HERPETOFAUNA SPECIES CLASSIFICATION FROM CAMERA TRAP IMAGES USING DEEP NEURAL NETWORK FOR CONSERVATION MONITORING

by

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DEDICATION

To my parents; a source of strength, endless support, and encouragement.

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ABSTRACT

Protection of endangered species requires continuous monitoring and updated information about the existence, location, and behavioral alterations in their habitat. Remotely activated camera or “camera traps” represent a reliable and effective photo documentation method of local population size, locomotion, and predator-prey relationships of wild species. However, Species recognition from gathered images is a challenging assignment due to a large amount of intra-class variability, viewpoint variation, lighting illumination, occlusion, background clutter, and deformation. Manual data processing from large volume of images and captured video is laborious, time-consuming, and expensive. There is an urgent need to establish a framework of automated wildlife species recognition by image classification. The recent advancement of deep learning methods has demonstrated significant outcomes for object and species identification in images. This thesis proposes an automated animal species recognition system by image classification using computer vision algorithms and machine learning techniques. The goal is to train and validate a convolutional neural network (CNN) architecture that will classify three herpetofauna species: snake, lizard, and toad from the camera trap samples.

The proposed solution offers two self-trained deep convolutional neural network (DCNN) classification algorithms CNN-1 and CNN-2, to solve binary and multiclass problem. The machine learning block of both architectures is same for the CNN-1 and CNN-2, while CNN-2 has been incorporated with several data augmentation processes

such as rotation, zoom, flip, and shift to the existing samples during the training period. Also, the impact of changing CNN parameters, optimizers, and regularization techniques on classification accuracy is investigated in this study. The initial experiment implies building a flexible binary and multiclass CNN architecture with labeled images accumulated from several online sources. Once the baseline model is formulated and tested with satisfactory accuracy, new camera trap imagery data is executed to the model for recognition purpose. All three species have classified individually regarding background samples to distinguish the presence of target species in a camera trap dataset. The performance is evaluated based on the classification accuracy within their group using two separate sets of validation and testing data. In the end, both models have tested to predict the category of a new example to compare the models' generalization ability with a challenging camera trap data.

1. INTRODUCTION

1.1 Motivation of The Research Work

Anthropogenic acquisition of natural resources and unplanned urbanization causes substantial changes in geographical patterns and earth's ecosystems. Due to massive landscape fragmentation, the overall habitat structure changes, which harms wildlife populations, habitat, and behavior. The two vertebrate classes, amphibia, and reptilia collectively referred to as the herpetofauna [1], are among the globally endangered species in conservation biology [2].

Since 1980, more than 120 species have been driven to extinction, and nearly one-third of amphibian species are now considered threatened worldwide [2]. Twenty years ago, researchers warned of habitat loss, and degradation as a primary threat to both amphibian and reptile populations [1] [24]. The author in [1] also cited habitat modification, introduced invasive species, disease, pollution, unsustainable use, and climate change as the six significant threats to reptile populations. In 2013, researchers presented the first global estimation of the conservation status conducted on 1,500 random reptile samples from all over the world [3]. Their assessment shown in Figure 1 indicates that agriculture (74% of threatened species affected), biological resource use (64%), urban expansion (34%), natural system alteration (25%), and invasive or problematic native species (22%) played as threats to reptile biodiversity [3].

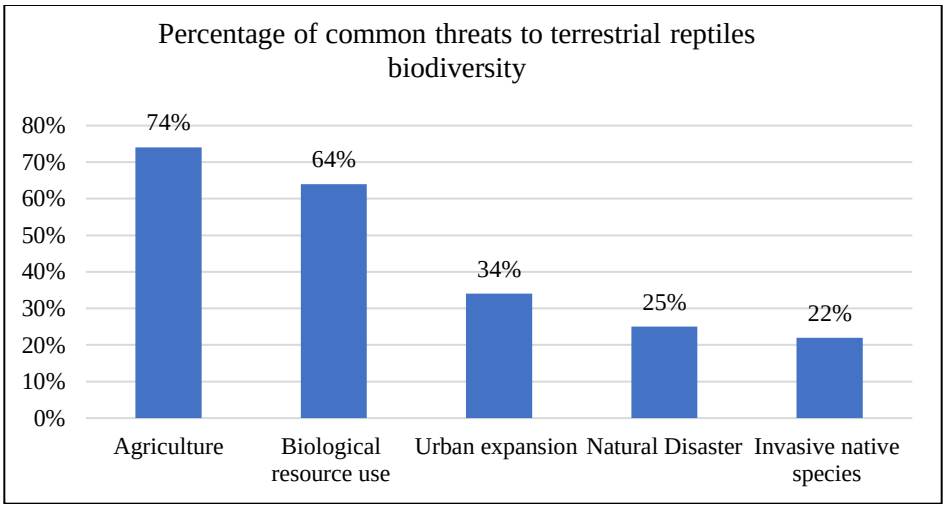


Figure 1: The percentage of threats by category impacting terrestrial reptiles estimated from 1,500 random sample from all over the world [3].

Several wild animal monitoring technologies have been developed by engineers and wildlife researchers, including radio-tracking [4], wireless sensor network tracking [5], and animal voice pattern recognition [6]. Very-high frequency (VHF) radio tracking, satellite tracking, and global positioning system (GPS) tracking are different forms of radio-tracking where information is transmitted through radio signals using devices [4].

Very-high frequency (VHF) provides good accuracy but has labor and weather dependencies [4]. Satellite tracking is less labor-intensive, but it is costly and comparatively less durable [4]. Moreover, all these methods are invasive as target species have to carry devices attached as collar or leg bend [4]. Furthermore, radio-tracking methods are not particularly applicable for the small species such as reptiles due to the body structure and difficulty in monitoring sufficient individuals. While very successful, voice pattern recognition can only be functional for toads/frogs as snakes and lizards (squamates) do not vocalize.

Data providing population size, dispersal, and the predator-prey relationships for endangered species are required to understand their distribution, as well as the threat processes' distribution [3]. Wildlife researchers have experienced that visual information provides definitive evidence of an animal's presence and activity analysis against environmental context [7]. The Department of Biology and The Ingram School of Engineering at Texas State University, and Texas A&M University work together in a "camera trap" project to identify species from images around the Texas. This thesis's outcome develops the basis of a mechanical structure to identify three broad groups of herpetofauna, toads/frogs, lizards, and snakes in camera trap images using computer vision and machine learning techniques.

1.2. Camera Traps in Wildlife Monitoring

Recent advancements in technology have allowed researchers to widespread the adoption of minimally invasive camera trap monitoring system. Motion-triggered remote cameras, commonly known as "camera traps," are gaining popularity for reliable and cost-effective applications [8]. Generally, camera traps are a static motion-sensor framework attached with some structure or trees in the field, pointing towards animal movement path [7]. The camera setup requires low labor engagement as it is quite simple to deploy, flexible to operate, and easy to maintain in the field [8]. Most importantly, the arrangement allows tracing the species secretly and continuously without disturbing their surroundings [5]. This powerful tool captures a rich set of information about animal appearance, actions, biometric features and provides critical evidence such as size can indicate the age of the animal, or entry angle reveals the direction of the animal's movement [7]. Additionally, camera traps enable associated metadata, such as date, time,

ambient temperature reading in images at the time of detection. Furthermore, even after data collection, the raw image data can be stored for future investigation. Below photograph in Figure 2 is an example of camera trap setup in Bastrop county using the Compact T70 camera.

(a)  (b) 

Figure 2: (a) A camera trap setup in Bastrop County, Texas, USA, (b) Compact T70 Camera that has been used to collect image data in Bastrop County, Texas.

1.3. Camera Traps in Herpetofauna Observation

Assessments of the camera trapping literature demonstrate that the camera trap has been primarily used for mammals, birds [9] [10], and fish [10]. The utility of camera traps for herpetofauna inspection is limited, especially for squamates (snake and lizards as a group). However, the camera trap monitoring for squamates has recently expanded [9] and is often used to supervise behavior or habitat [10]. Authors in [11] reviewed 266 studies published on camera trapping between 2008 and 2013 and observed that till then, only five studies were focused on herpetofauna species [10]. The below table 1 depicts the comparison of camera trap execution according to the target species where studies were focused on mammal species 94.8%, birds represented 11.9%, a few studies included reptiles (11%), amphibians (74%), and plants (74%) [11].

Table 1: Percentages of camera trap publication focused on certain group of species from 226 sample study [11].

Target Group	Percentage of publication about certain group of species among 226 camera trapping publication
Mammal	94.80%
Birds	11.90%
Reptiles	1.10%
Amphibians	0.74%
Plants	0.74%

Among the species group, amphibians have been monitored on a small scale for their ectothermy (relatively small or quite negligible internal physiological sources of heat) attribute and small body size [10]. Usually, trail cameras use a passive infrared (PIR) sensor designed to detect species based on a combination of heat and motion [12]. A PIR trigger requires a minimum thermal contrast between the target and the background [9,12]. Normally, the temperature between the ectothermic animal and their surrounding environment seldom varies greater than 3˚C [12], which may hinder the detection process of herpetofauna species via PIR mode.

Furthermore, body mass and the distance between animals and cameras determine the magnitude of infrared radiation, influencing the camera trigger to capture images [12]. The monitoring of squamate group faces a similar limitation [10], but it overcomes the problem by programming the camera to trigger time-lapse instead of the PIR system. In a time-lapse system, the camera is programmed to capture images over a scheduled time interval. Researchers have also adopted new techniques such as deploying cameras near drift fences with pitfall traps [10], as shown in Figure 3. The drift fence concept stands with the assumption that it will allow squamates to move slowly across the target area [25].

(a)  (b) 

Figure 3: (a) An example of drift fence setup deployed in Bastrop County, Texas, and (b) a snake is passing through a drift fence.

1.4. Challenges with Camera Trap Images

Despite various advantages of camera trap data, getting a quality image is challenging due to significant intra-class variation of species, unpredictable pose, lighting brightness variation, motion blurriness, and cluttered background [13] [14]. The waving trees, moving shadows, and sunspots make images dynamic, which leads to difficulties in distinguishing the animals from leaves, grass, and branches [7] [14]. Moreover, the appearance of several species in one single image, partially displayed or cropped out the body and extremely far or close from the camera, creates high complexity to recognize the desired object [15]. Furthermore, most of the species have natural camouflage capability that create an obstacle to collect objective features [14]. Therefore, it is a challenge to process the recorded images and identify the species from a photograph [15]. The images in Figure 4 display some examples of the challenges associated with the camera trap dataset collected from Foxhunter's Hill in the Sabine National Forest in eastern Texas, USA [25].

(a) 

(b) 

(c) 

(d) 

Figure 4: Some of the challenging pictures from camera trap data, (a) night vision image of toad having lighting brightness variation, (b) a lizard image having natural camouflage, (c) image of a snake displaying partial body in highly cluttered background, and (d) target species is very small to detect in background.

Also, manual species identification methods are debatable as the process may suffer unavoidable bias when analyzed by a human from camera trap data [16]. The automatic classification of camera trap images has been emphasized in research in the field of computer vision and machine learning to address these concerns.

1.5 Camera Trap Data Processing with DCNN

This research proposes a deep learning approach that can execute an optimized machine vision assignment with a large camera trap image dataset. With the recent advancement in computation and deep learning, a modern machine learning technique demonstrates promise for automating the data analysis in computer vision tasks. Deep CNN has high feature learning capacity and has shown robustness to classify objects in

challenging images. This method offers tremendous opportunities for automated species identification from a high volume of biological image data.

The aim of the thesis is to build a structure that will recognize and classify frogs/toads, snakes, and lizards from a given set of a large camera trap dataset collected from different locations within Texas. Building a machine learning model involves following steps, as shown in Figure 5.

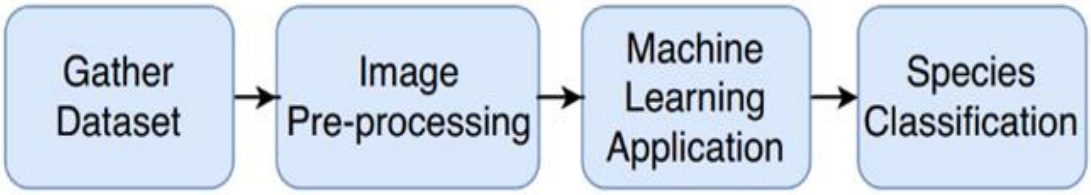


Figure 5: An overall workflow diagram of the research work having four major steps of image classification procedure using DCNN algorithm.

1.6 Thesis Outline

This thesis is organized as follows. Chapter II describes about the previous initiatives taken by Texas State University to protect endangered species, a little introduction about citizen science projects and ImageNet challenges. In Chapter III, a detailed literature review based on the previous work related to species classification with DCNN has been highlighted. In Chapter IV, thesis design approach and classification pipeline have been explained in short. Chapter V talks about data accusation, and characteristic of both datasets: online and camera trap with some example images. Chapter VI entails all about DCNN building block and architecture. Chapter VII is the methodology chapter of the research work that describes data preprocessing, data partitioning and the model architectures. Chapter VIII discusses the experiment and results analysis. Finally, Chapter IX summarizes the overall research contributions, and the possible future research.

2. BACKGROUND

2.1 Camera Trap Project Initialization by Texas State University

An array of research conducted by the Department of Biology of Texas State University pursues the inventory of the relative density, distribution of herpetofauna community, and herpetological assemblage using standard sampling technique within Texas [19]. The researchers of the Biology department have actively performed several investigations to understand the motive behind herpetofauna population decline; such as Allee effects of a correlation between population density and the mean individual fitness in the conservation of endangered anurans, [20] or the impact of natural calamities such as drought and wildfire on herpetofauna species [21]. In the past few years, they are experimenting with 'Toad Phone' development projects in collaboration with the Ingram School of Engineering. That project aims to trace the Houston toad (*Bufo houstonensis*) breeding activity using Automated Recording Devices (ARD's) that store environmental information and send notifications in near real-time [22][23]. However, only male amphibians chorus. Therefore, image data collected by the camera traps presents new diagnostic opportunities to detect and monitor species, including females of the amphibians and other herpetofauna.

The camera trap data has been utilized since 2004 to complement the amphibian and other species detection process. In 2019, fourteen cameras were attached near drift fence arrays in Bastrop County, Texas, where data was collected five times from September to December. Each camera captured roughly 10,000 images stored in a 32 GB SD card resulting in millions of images. Though these cameras provide a large volume of serialized data, less than 1% of the images are likely to have valuable information such as

species' presence, and the remaining images only contain background environmental information. Among those species' images, it can be expected that about one-tenth of the images might have any of the three target groups of interest. Due to the unavailability of computation framework, data had to be analyzed manually. Distinguishing empty frames and target species from a vast dataset are still done by human reviewers, which is a monotonous and time-consuming task. For the assessment of the extensive database, an automatic system should be established, allowing researchers to focus only on essential analyses and evaluation of animal detections.

A reliable object recognition framework is needed to provide substantial time saving procedures to manage large image datasets. The modern machine learning approach is gradually paving into the field of species identification. The theory and the mathematical foundations for neural network were laid several decades ago [17]. The availability of massive datasets, advancement of raw compute power, and efficient parallel hardware have contributed to the rise of machine learning applications [17] [18]. The potentiality of computer vision technology and deep neural network to classify images has provided an improved wildlife monitoring system reducing classification time and manual effort.

2.2 Citizen Science Projects

Researchers seek data to evaluate the biodiversity crisis and to understand the impacts of human actions or natural environmental changes to create effective resource management decisions and stewardship of wildlife species. In recent years, ecologists, biologists, engineers, researchers, and volunteers collaborate in citizen science (also known as crowd-sourced) projects to support wildlife monitoring and research. For

example, ‘Zooniverse’ is the largest people-powered research community where millions of volunteers assist professional researchers in producing reliable and accurate data by labeling, and analyzing images [27]. This online platform provides standard guidelines and annotation tools to the researcher to extract information more quickly and accurately [26]. Until October 2019, Zooniverse has hosted 111 camera trap projects, producing millions of images of wild species worldwide, and citizen scientists are analyzing data remotely via web-based image classification systems [27]. The first camera trap project Snapshot Serengeti (SS) contains images of 48 animal species acquired from 225 cameras placed in Serengeti National Park, Tanzania [26].

Traditionally, species classification is being conducted by morphological diagnostic process provided by taxonomic studies specialists which requires skills obtained through extensive experience [28]. However, the researchers realized the need for automated and accurate identification methods over time [28]. The modern artificial intelligence systems are providing an alternative tool for identification tasks [28]. A couple of studies have been done with a crowdsourced camera trap dataset applying deep neural network in the last few years. The outcome portrays the ability to extract valuable knowledge from camera trap images using deep neural networks (DNNs). Some of the studies regarding the camera trap citizen science project will be highlighted in the literature review chapter

2.3 Pre-trained Deep Learning Models

In the machine vision research field, an organized large-scale image database is necessary with the facility of web-based data storage. The “ImageNet” project facilitates millions of labeled and categorized images for the computer vision and deep learning

communities [17]. This platform has recently hosted the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) annual competition from 2010 to 2017. The main challenges were image classification, single-object localization, and object detection using 1,000 categories from the ImageNet dataset [17]. The accuracy of the winning ILSVRC has improved significantly every year, showcasing the progress in terms of state-of-the-art performance. The deep convolutional neural networks (DCNNs) architectures achieved tremendous success overtime in object classification, object localization, and object detection as represented in the below Figure 6 [29][30][39]. AlexNet, ZF Net, GoogLenet, VGGNet, and ResNets architectures were developed by the winner or runner up teams of the ImageNet competition from ILSVRC2012 to ILSVRC2015 consecutively [31][39]. Considerable research has been performed with camera trap dataset applying pre-trained architectures (transfer learning techniques) in the last few years as described in literature review section.

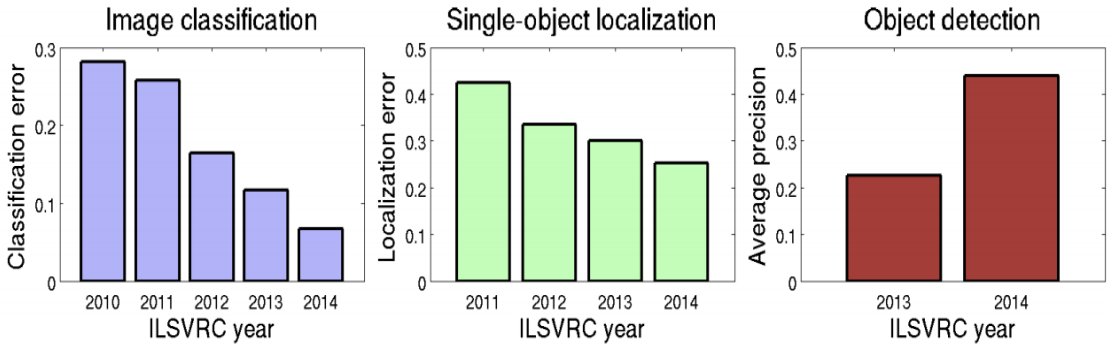


Figure 6: Performance improvement of winning participants of ILSVRC2010-2014 competitions for three tasks; Image classification, Single-object localization, and Object detection illustrating the reduction of error for 1.2 million training images having 1000 object categories [39].

3. LITERATURE REVIEW

This chapter provides a literature survey of research work that focuses on identifying species using machine vision techniques and deep learning technique published in various conference and journal papers. The majority of the research work on plant or animal species recognition have been performed with image samples taken by digital cameras in labs or natural habitats. However, numerous species recognition experiments with camera trap image have been conducted recently, mostly for mammals and bird group, and more research is getting published with gradual improvement over time. In the subsequent paragraphs, some of the academic research for camera trap image identification using the different techniques are discussed. Also, some of the experiments with target species using online data have been considered for review.

3.1 Species Identification Using Feature Extractor and Classifier

Most of the camera-based wildlife experiments are done to identify individual animals with unique coat patterns such as spots, stripes [32], shape, and texture [33]. In past years, different algorithms were used as *feature extractors* or *image descriptors* to obtain features such as shape, texture, color from input images, and quantify the individual aspect with statistical analysis [33, 16]. The traditional image classification process consists of a hand-defined feature extraction algorithm, followed by a machine learning classifier [33]. On the other hand, the deep learning networks approach automatically learns features from input images in the training process, eliminating rules and algorithms to extract features [33].

Studies suggest that ten years ago, *bag-of-features* (BoF) was the utmost popular image categorization task [34, 35]. Authors in [34, 35] classified BOF along with *spatial*

pyramid matching (SPM) as a *state-of-the-art image classification system.* In 2013, the first complete analysis with a camera trap dataset was done by authors in [32] using the Scale-Invariant Feature Transformation (SIFT) algorithm in combination with a Support Vector Machine (SVM) to classify species. The researchers collected seven thousand camera trap images of 18 species from two different field sites for the experiment that achieved an average classification accuracy of 82%. The authors applied improved sparse coding spatial pyramid matching (ScSPM), SIFT descriptor, and cell-structured local binary patterns (cLBP). Feature generation was done by weighted sparse coding and max pooling using multi-scale pyramid kernel, and classification of the images was done by linear support vector machine (SVM) algorithm.

3.2. Camera Trap Dataset with Deep Neural Network

In 2014, the first CNN application can be observed in [5] where the authors presented a comparison of results between two-image classification algorithms, Bag of Visual Words (BOW) and DCNN. The dataset contains 20 species having 14,346 training images and 9,530 testing images. In the BOW method, a 128-dimensional Scale-invariant feature transform (SIFT) algorithm was used to extract the feature, and linear SVM was used as a classifier. On the other hand, three convolutional layers and three max-pooling layers were implemented in the DCNN method with a data augmentation step in the training stage. With a very challenging noisy dataset, DCCN showed promising results with 38.315% accuracy, where BOW's accuracy was 33.507%.

The ILSVRC DCNN model architecture from ImageNet competition has provided a dominant win over traditional algorithms [5]. Moreover, the publicly available citizen science dataset has opened an opportunity to do more research for camera trap data using

DCNN. In 2016, eight variations of CNN frameworks AlexNet, VGGNet, GoogLenet, and ResNets were used to identify 26 classes of animal species from highly unbalanced Snapshot Serengeti dataset [15]. The number of layers of the mentioned CNN architectures varied from eight (AlexNet) to 152 (ResNet-152), where ResNet-101 architecture achieved the best performance [15].

In the research found in [36], the authors also experimented with nine independent architectures, including AlexNet, NiN, VGG, GoogLeNet, and numerous variations of ResNets with 48 species in the 3.2-million-images of Snapshot Serengeti dataset. Also, to detect species, authors have trained the model to identify further attributes; presence, counting, and behaviors (the presence of young). Similar work has been found in [29], where authors reviewed different CNN architecture (AlexNet, VGGNet, and ResNets) in automatic identification for two subsequent tasks: (a) filter images containing animal from a set of Wildlife Spotter project dataset, (b) then classifying species automatically. The model achieved more than 96% in recognizing animals in images and close to 90% in identifying three common animals (*bird*, *rat*, *bandicoot*).

In 2018, authors in [16] compared the performance of two algorithms Faster Region-Convolutional Neural Network and You-Only-Look-Once v2.0, to identify and quantify animal species on two different datasets; *Reconyx Camera Trap* and the self-labeled *Gold Standard Snapshot Serengeti* data sets. The findings demonstrated that YOLO has speed advantages and can be used in real-time performance, whereas Faster R-CNN represented promising results with average accuracy of 76.7% and 93.0%, respectively.

Authors in [37] trained 3,367,383 camera trap images from five states across the United States with convolutional neural networks with the ResNet-18 architecture providing 98%, which is the highest accuracy to date. Recently authors in [38] have trained 8,368 images having six categories: badger, bird, cat, fox, rat, and rabbit with two different networks; a self-trained framework (CNN-1) and pre-trained model AlexNet (CNN-2) where CNN-2 outperformed CNN-1.

3.3 Target Species Recognition Using Deep Neural Network

Most Recently, few recognition experiments of target species (snake and lizard) have been conducted using online dataset applying deep learning techniques. So far, no work has been found focusing on toad/frog detection from images using deep learning technique.

In the research found in [14], lizard was detected and counted from drone images applying pixel-wise image segmentation deep learning approach "U-Net". The author had to train the model with 600 online datasets as the captured images by drone did not provide sufficient sample to do the experiment. The highest validation accuracy the model achieved is 98.63% using a batch normalization in atrous blocks of the U-Net model.

In 2018, authors in [76] classified five venomous snake species in Indonesia with 415 samples. The authors performed the experiment with three different self-trained CNN models; shallow, medium, and deep CNN architectures by changing filter size and by adding more layers. With the five-fold cross-validation process, the medium architecture offered the best performance with an average accuracy of 82%.

For the work in [77], experiments have been performed a real-time identification of snakes of the Galápagos Islands, Ecuador by applying object detection and image classification approach. Four region-based convolutional neural network (R-CNN) architectures have been tested for object detection: Inception V2, ResNet, MobileNet, and VGG16. The experiment studied 247 snake images of 9 species where ResNet achieved the best classification accuracy of 75%, Inception V2, and VGG16 scored 70% for the given dataset.

In 2020, the LifeCLEF research platform arranged a four round *SnakeCLEF 2020 challenge* focusing on the automated snake identification from large online dataset [78]. The task of this experiment was to distinguish 783 different snake species from 245,185 training and 14,029 validation samples [78]. As an object detection method, the researchers in paper [78] used Mask Region-based Convolutional Neural Network (Mask R-CNN) with EfficientNets for classification and associated location information of the samples. The initial result with the best model achieved a macro-averaging F1-score of 0.404 that has been improved afterword with a macro-averaging F1-score of 0.594.

3.4 Thesis Contributions

After research, it can state that this is the first attempt to recognize herpetofauna, especially snake, frog/toad, with a DCNN approach from camera trap images. This project intends to work with different CNN architectures with both online datasets (collected from the internet) and a camera trap dataset (collected from the field). Previous experiments, assessment, and analysis of the works suggest that DCNN is a suitable technique to extract valuable knowledge from images.

The goals of this study are -

(a) To present an automated framework of photo identification for animal species by constructing, testing, refining an image classification algorithm for both sample sets; online dataset and camera trap dataset.

(b) To investigate several image pre-processing solutions to mitigate challenges in the dataset by applying image augmentation techniques.

4. THESIS IMPLEMENTATION STRATEGY

The ultimate thesis's objective is to develop a computer vision and machine learning solution that will classify all three species (snakes, lizards, and frogs) individually and separately in different pictures. In image classification, the core task is to assign a label to an image from a predefined set of possible categories. The workflow of methodology starts with collecting samples, preprocessing datasets, training a CNN model architecture, and evaluating the classifier on a withheld set of test images. Figure 7 shows an overview process of the proposed design approach.

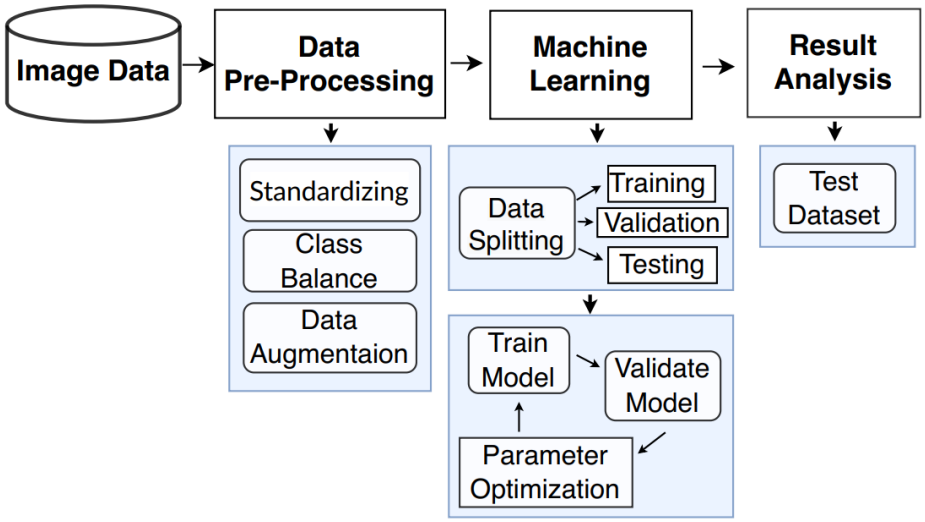


Figure 7: An image classification pipeline using DCNN techniques representing four main steps.

Two different CNN architecture referred as CNN-1 and CNN-2 have been constructed and later have been trained, evaluated, and compared under the given datasets. The fundamental building block of the DCNN framework, which is layers, parameters are the same for both models. The only difference between the two models is applying several data augmentation techniques in the second model to artificially enlarge the size of a training dataset by creating modified versions of images. The basic idea is to

compare the generalization ability of two models for a new set of the testing dataset in the evaluation period. An elaborate explanation of sample augmentation methods has been described in Chapter VII. The main building block of the two models is picturized in Figure 8.

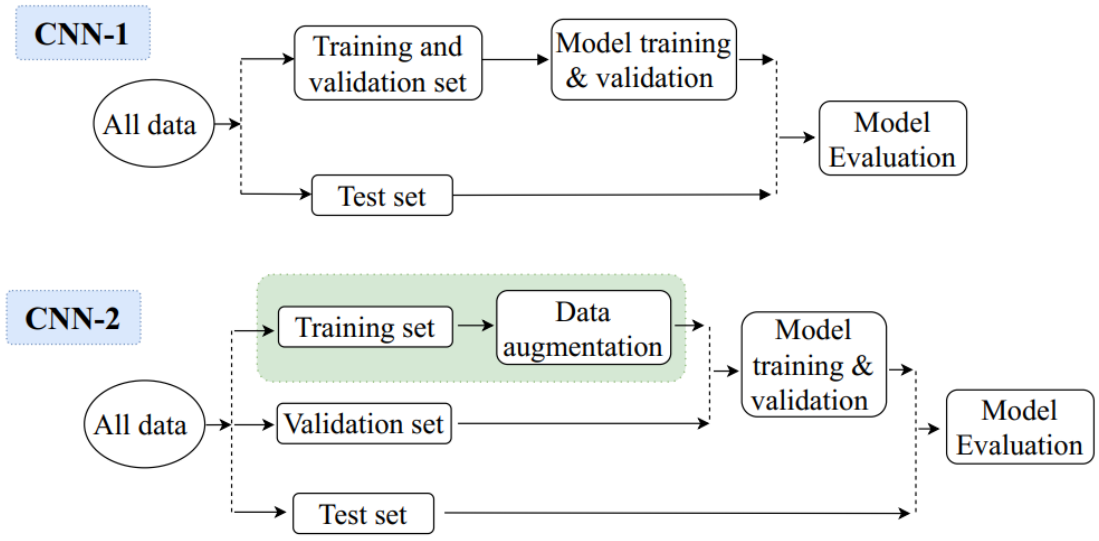


Figure 8: Building blocks of CNN-1 and CNN-2 where CNN-2 have an added augmentation step for the training data with different transformation techniques.

For the convenience of the experiment, the model implementation is divided into two phases as defined below.

Phase one: The first phase comprises developing a baseline model from scratch to classify species from images, not necessarily camera trap data. This phase applies the dataset of 13,500 target species samples collected from various web database sources. The first phase is a primary learning stage where two basic CNN architecture has formed with several layers and combination of hyperparameters. Both the models have been trained with the assembled dataset and were evaluated by the ability to separate species into their category. Through several analysis and performance testing, gradual improvements have been made in the model construction over time.

The model design was formed into several techniques to accomplish the identification process in an efficient way.

(a) **combinations of any two species:** Both architectures have been designed to solve a classical binary classification problem where the prediction result was measured for any two classes, such as snake-lizard or toad-snake. This task involves training, validation, and testing photos containing only two animal species at a time.

(b) **combination of all three species:** This structure considers a multiclass recognition formation with all three species. The algorithm has trained with single labeled three category images altogether, and the output provides classification accuracy for three species. The models have experienced necessary changes, especially in hyperparameters such as loss function, learning rate, and other network parameters.

Phase two: In the second phase, both the models were equipped with imagery camera trap data. Here, the previous models were used to train new data where several hyperparameter adjustments have been made according to the camera trap image identification process. Similar to phase one; first the execution was tested with the combinations of any two species, and later each of the models was performed for all three species.

For each technique, every architecture will be customized to show a high prediction probability for the test dataset. The network architecture needed to tune with several hyperparameters such as learning rate, activation fiction, epoch size, batch size, number of units, and other parameters to obtain optimal performance. The final model was chosen carefully considering the highest classification accuracy for all their species

together model approach. Figure 9 provides an overall frame of the thesis implementation approach.

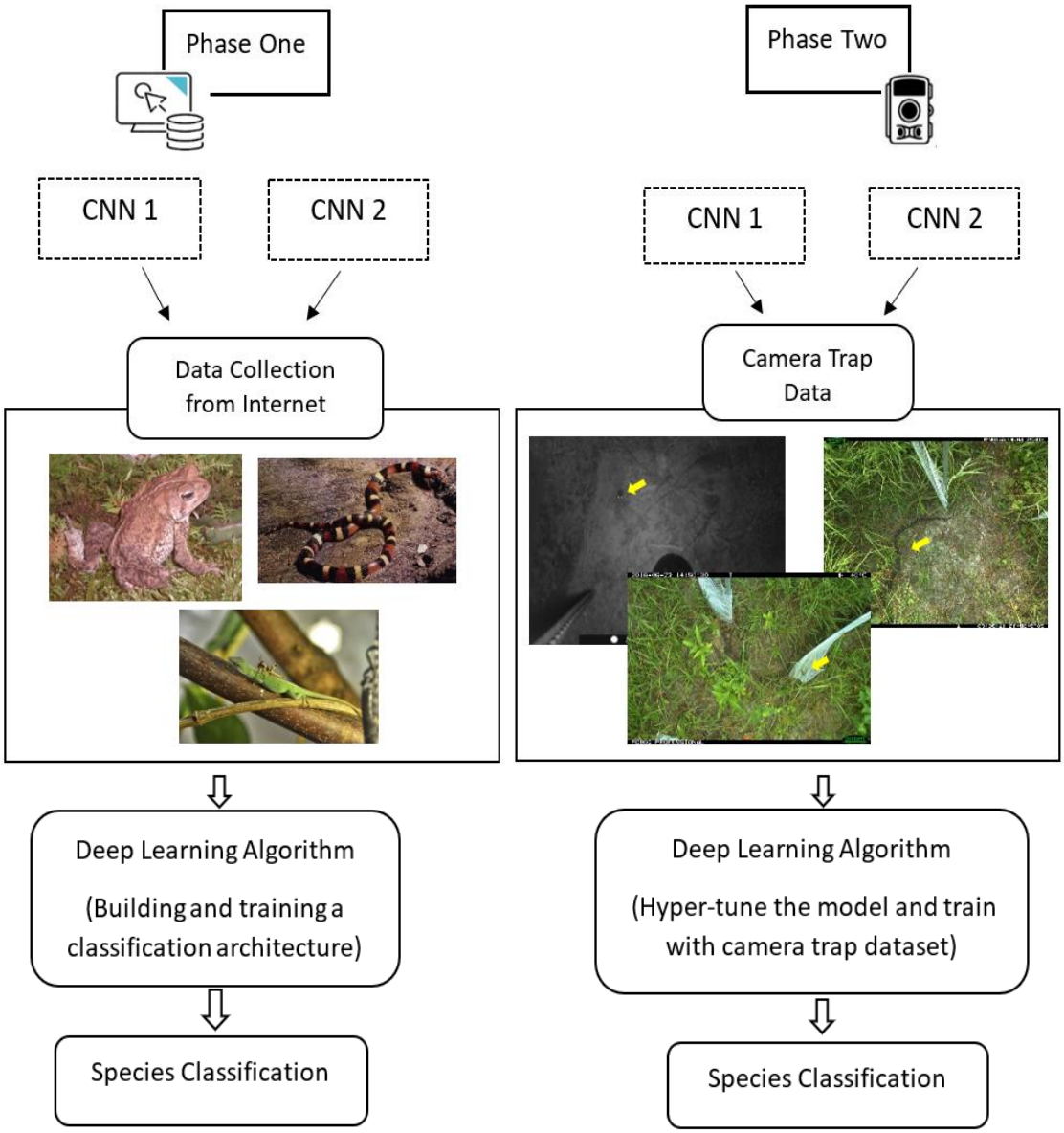


Figure 9: Thesis implementation strategy overview for phase one (pictures from [43], [44]) and phase two that will be implemented for two models (CNN-1 and CNN-2).

5. DATASET

For image classification problem, the dataset refers to a collection of images where each image is a data point [33]. Machine learning algorithms are heavily dependent on the size of dataset [40]. Elaborately, the algorithm's learning ability is determined by the amount of quality information that holds the key factor of an image [33]. A useful dataset is essential to prepare a CNN model to perform the classification task when unobserved data is given. In this project, most of the research time is allocated to accumulate and preprocess datasets. The subsequent subsections describe data gathering process, sources, characteristics, and changes of two kinds of dataset: online dataset (phase one) and camera trap dataset (phase two).

5.1 Online Dataset (Phase One)

5.1.1 Data Accumulation

For this project's initial experiment, 13,500 photographs of snake, lizard, and toad/frog were collected from various online sources. Most of the images have been collected from standard benchmark datasets such as Caltech, CalPhotos, and Open Images. In contrast, some photos have been collected from image classification challenge [67] and the online photo archive [44], [75]. “CalPhotos,” is an online image database specialized in plants, animals, and natural history [41]. This database is a project of Berkeley Natural History Museums and the University of California, where images are stored with descriptive information about scientific and common names, locations, dates, and contributor’s information [41].

Open Image is one of the largest online databases released by google dedicated to image classification and object detection. The web portal contains 600 object categories

of images annotated with labels, object bounding boxes, object segmentation masks, and localized narratives [42]. Around 2,000 snake, toad and lizard images have been downloaded from Open Images V6 following their instructions. Also, 500 snake and frog image data were stored from Caltech, a standard public dataset [43].

Nearly 1,000 images were accumulated from the Bing Image Search API that facilitates custom search images provided by the Microsoft Bing web portal [45]. Another 1,000 images have been gathered from a crowdsourced online website Unsplash and Pixabay [44], [75]. However, acquired images from Microsoft Bing needed manual examination to clean unwanted samples of target species such as animation, graphics, or sketch.

5.1.2 Specifications of Online Dataset

The downloaded dataset portrays that most of the subject species are free-living animals where images are captured in an open environment. Some of the pictures are captured in laboratory settings. In phase one, target animal species have been chosen with numerous variations of color, size, and background to let the model learn the features properly. The animal body was visible about 20-80% of the whole pixelated area of an image. However, those images suffer from dynamic object position, light illumination, occlusion, complex animal poses, and significant intra-class variation within their group. Below samples in Figure 10, 11, 12, 13 show some of the attributes that have been considered while building the CNN model.

Figure 10: Samples of (a) snake, (b) lizard, (c) frog/toad images collected from Pixabay, Unsplash, and Caltech database [43], [44], [75]. The examples have high intra-class variation with different body size, color, shape, texture, lighting illumination and dynamic animal pose.

Figure 11: Samples of (a) frog/toad, (b) snake, (c) lizard images from online dataset [43], [44], [75] presenting challenges such as confusing body color with nature having high camouflage effect.

Figure 12: Samples of (a) frog/toad, (b) snake, (c) lizard images from online dataset [43], [44], [75] showing partially body size and occlusion by leaf or background.

(a)  (b)  (c) 

Figure 13: Samples of (a) frog/toad, (b) snake, (c) lizard images from online dataset [43], [44], [75] displaying inter class similarities of species.

5.2 Camera Trap Dataset (Phase Two)

5.2.1 Data Accumulation

Researchers at Texas A&M University have conducted camera trap experiment to study the diversity of animal species, primarily terrestrial squamate. Images were captured in time-lapse triggered mode in two suitable locations in the area known as Foxhunter's Hill in the Sabine National Forest in eastern Texas, USA [25]. The RECONYX PC800TM model camera was used to collect photos [25]. The camera was attached with a 3 m (~10 ft) piece of metal conduit, positioning the lens down towards the background [25] as in Figure 14. Each camera was operated by twelve Energizer Lithium-Ion batteries [25]. The data was stored with Verbatim Premium 32 gigabyte SD cards [25].

Figure 14. An example of camera trap design deployed in longleaf pine habitat, Texas [25].

The cameras were programmed to capture an image in every 30 seconds, that produced thousands of images [25]. However, the given dataset for this project has ~ 700 snake, ~ 600 toad, and ~ 2,000 lizard images. Among those images, sometimes, a single target species was found in 5-150 consecutive pictures, especially lizard and toad data. Table 2 provides several toad/frog, snake, and lizard individuals with their scientific names that have been used as the dataset for phase two.

Table 2: Camera trap data of toad/frog, lizard, snake with their variety of taxon provided for phase two dataset including data quantity for each target group.

Target Species	**Scientific name**	**Number of animal species approximate**
Toad/Frog	*Bufonidae* *Incilius nebulifer* *Ranidae* *Lithobates sphenocephala*	600
Lizard	***Anolis carolinensis*** *Aspidoscelis sexlineata* *Scincella lateralis* *Scincidae* *Unknown lizard* *Sceloporus consobrinus*	2,000
Snake	*Virginia striatula* *Micrurus tener* *Masticophis flagellum* *Pantherophis obsoletus* *Storeria dekayi* *Pantherophis obsoletus* *Storeria dekayi* *Thamnophis proximus* *Pantherophis slowinskii* *Coluber constrictor* *Heterodon platirhinos* *Lampropeltis calligaster* *Agkistrodon piscivorus* *Heterodon platirhinos*	700

The Table 2 illustrates the diversity of samples in the camera trap dataset. From the above table it can be noticed that the dataset poses a wide variation of 15 categories snake species. All the snake categories contain a variety of body shape, size, color, and

background. On the other hand, there are four kinds of toad species which consist nearly similar body size, shape, and color. Though the lizard dataset comprises numerous categories, only *Anolis carolinensis* was considered for the classification experiment. The reason is that the other lizard taxon exhibits severe difficulty to distinguish from background due to the confusing body size and color. Among the 2,000 *Anolis carolinensis lizard,* around 1,800 samples were chosen for experiment where the lizards were noticeable in the background.

5.2.2. Specifications of Camera Trap Dataset

The camera trap dataset of three species has many divergences according to their body shape, size, habitual trait, and behavioral attribute. In some cases, three of the species pictures shares some typical pattern too. Below notes shows the collective attributes of the dataset, which makes the dataset diverse and challenging -

1. Most of the camera trap images have a resolution of 1,920x1,080 or 2,048x1,536 for the three species. Among them, snakes cover 5% to 15% pixelated of the whole images depending on their body size. The lizards have a dynamic body poster consuming 0.025% - 0.35% of the whole image background. On the other hand, almost all the toad has a similar body shape in the images containing 0.7% - 0.16% representation area.
2. Most of the imagery data captured by the camera traps are serialized image of same species within their background, specially lizard and toad. A snake appears in images with the sequence length ranging from 3 - 15 frames where toad and lizard occupy 20 - 150 frames in a row in the dataset.

3. Day images have more alteration in the background due to changing brightness illumination over the day. Night vision pictures provide an advantage of less cluttered background as IR mode produces grayscale images offering less lighting intensity variation.

Some of the sample images of camera trap dataset are attached below in Figure 15, 16, 17 for better understanding.

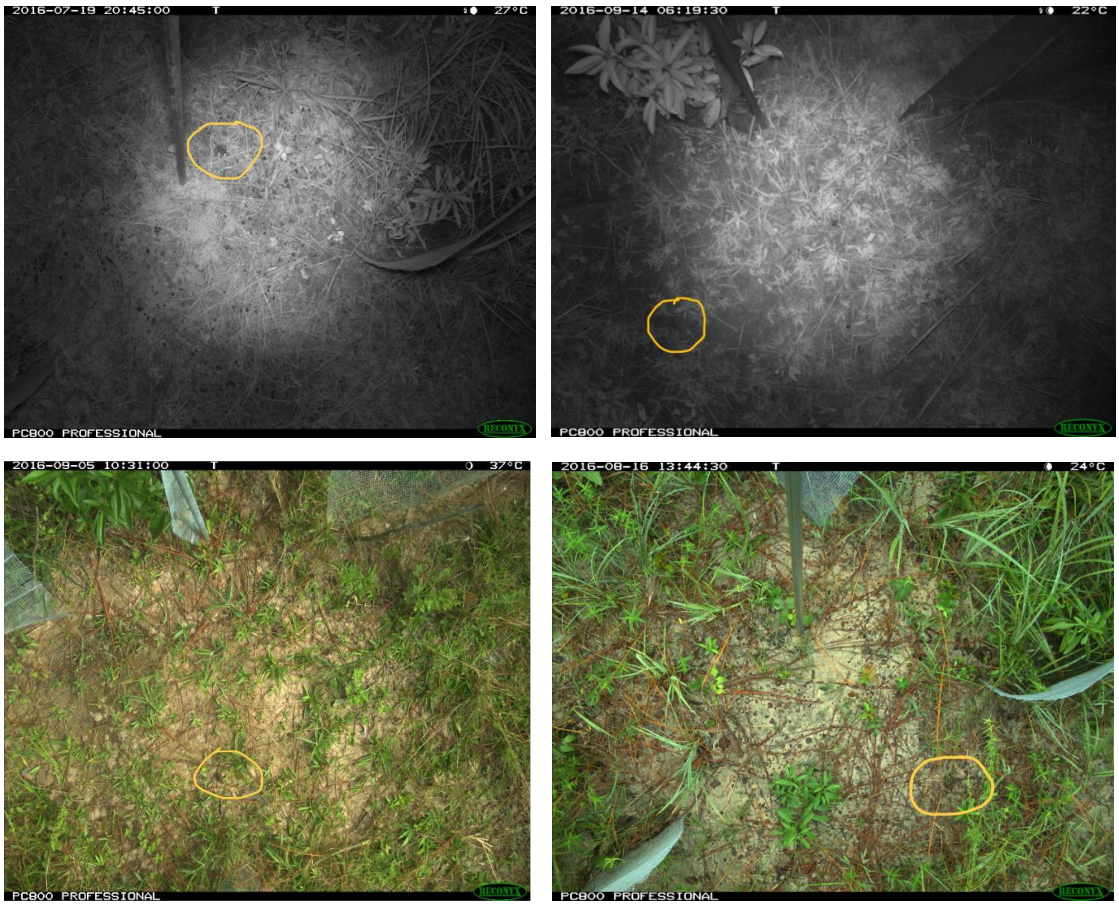


Figure 15: Samples of frog/toad from camera trap images having different challenges such as small body size, cluttered background, confusing body color with nature, or hiding body part behind leaf.

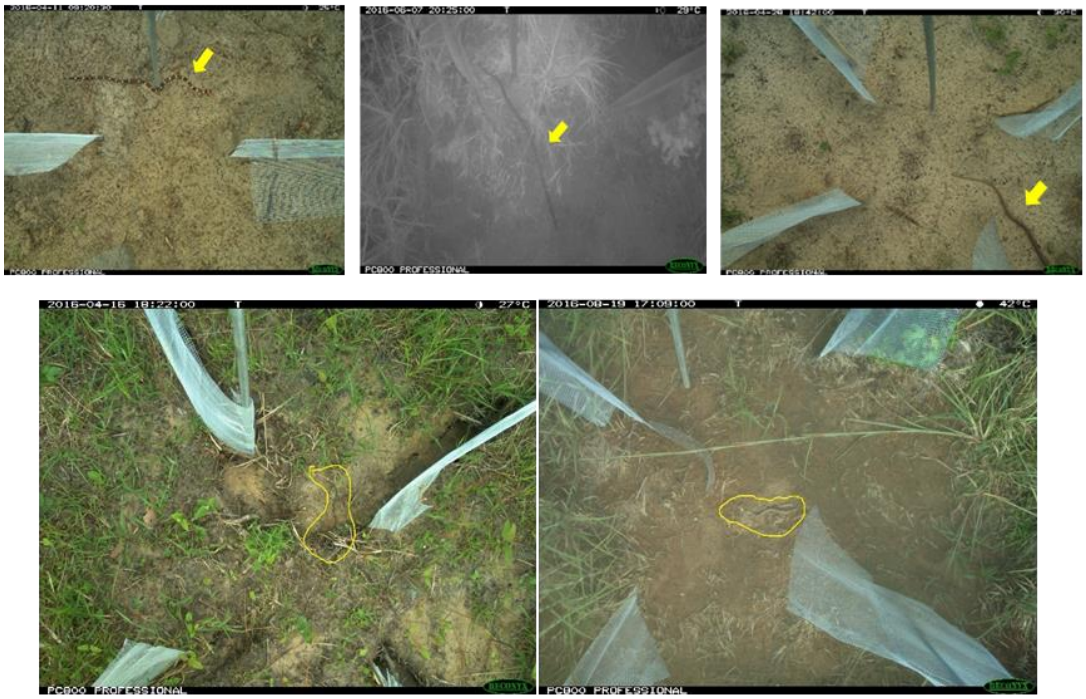


Figure 16: Samples of snake from camera trap images dataset having different body size, confusing body color with nature, or hiding body part behind leaf.

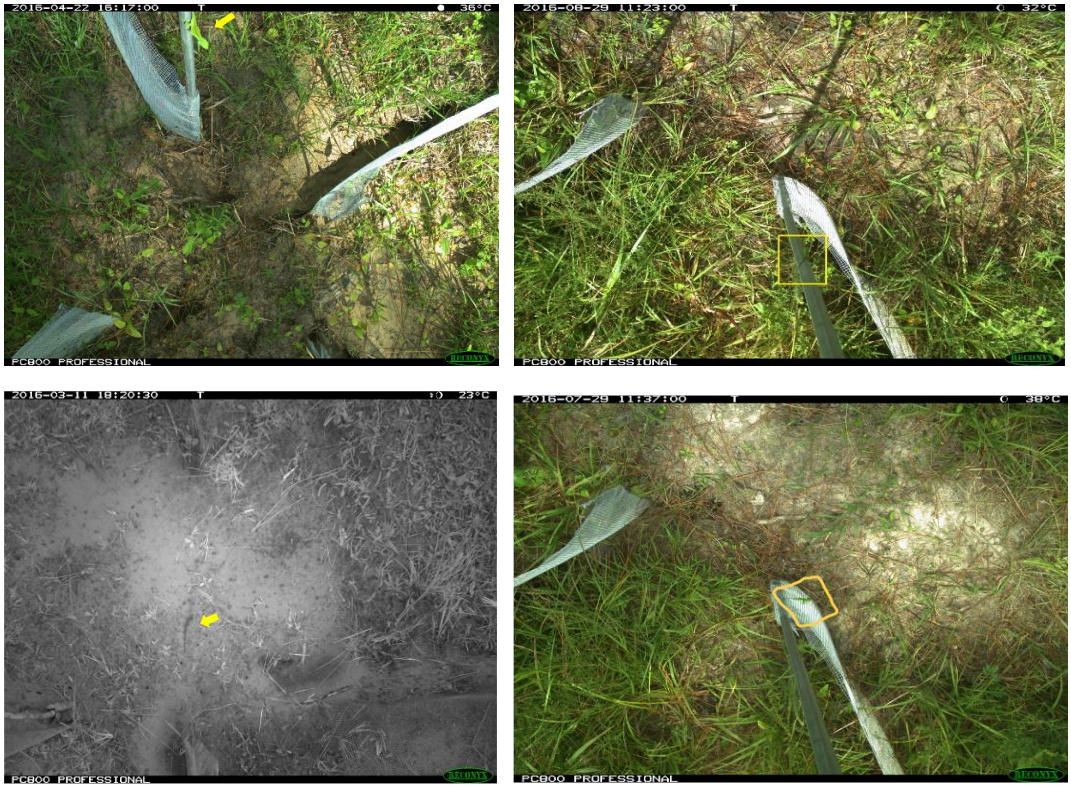


Figure 17: Samples of lizard from camera trap images having different challenges such as small body size, cluttered background, confusing body color with nature, or hiding body part behind leaf

6. DEEP LEARNING

6.1 Artificial Neural Network

Artificial neural network (ANN) is a supervised learning technique built with many of artificial unit components named “neurons.” Neurons are organized in interconnected layers where each neuron can make simple decisions and transfer those decisions to other neurons. The architecture uses different layers to learn aspects, recognize patterns, and analyze different factors similar to the human neural system [46]. Machine learning (ML) algorithms, neural networks, and deep learning fall into the domain of Artificial intelligence (AI) as shown in the Figure 18.

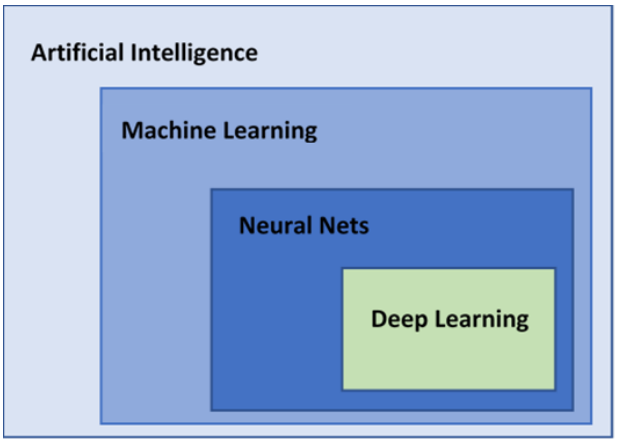


Figure 18. A Venn diagram describing relationship between artificial intelligence, machine learning, neural networks, and deep learning.

Artificial intelligence (AI): AI is a broader concept which builds intelligent programs and machines that can creatively solve problems [46].

Machine learning (ML): ML is a subfield of AI providing a system to learn and improve automatically from experience through an explicit program with minimal human interaction [46]. The algorithm can understand the relationship between input-output data and predict the value or the class when a new data point is given [47]. In ML, a neural

network or deep neural network is a widely used technique to handle large parameter problems in a non-linear approach.

Neural Networks: Neural networks are a subfield of machine learning that works excellent where the volume of data and the number of variables or diversity of the data is massive [48]. The basic idea of a neural network is that it can depict associations and discover consistencies within a set of patterns from data.

Deep Learning: Deep learning is nothing but a richer structure of a neural network. Deep learning is considered as the new state of the art in the territory of artificial intelligence [47]. These are multi-level structures that extract detailed information from input data such as patterns, speech, images, and other applications.

There are a few reasons behind the growth of ANNs over other ML techniques on substantial and complex problems [50]. A tremendous improvement can be noticed in the device capabilities such as memory capacity, power consumption, image sensor resolution, and optics [52]. Since the 1990's, computing power surged incredibly, making it feasible to train large neural networks in a reasonable amount of time [50]. Moreover, powerful GPU cards are available due to the progression of the gaming industry [50]. Deep neural networks can drastically reduce model execution time by taking advantage of GPU for computation. Furthermore, the data availability in huge quantities adds an impact to train a neural network. All the factors together lead researchers to focus more on DNN, which eventually improves the training algorithm over time. Thus, the deep learning performance has been upgraded, providing cost-efficiency and speed acceleration of vision-based applications [50].

The structure of neural networks is simulated by the information processing patterns of the human brain [33,49]. A typical brain contains millions of neurons (basic computational unit) connected with synapses. A neuron receives input signals from numerous dendrites and produces output signals towards the axon. The end of axon branches is out to connect with dendrites of other neurons via synapses. The neuron only triggers and sends a spike through the axon when the combination of input signals from dendrites reaches some threshold condition. Figure 19 compares a biological neuron with a basic mathematical model [49].

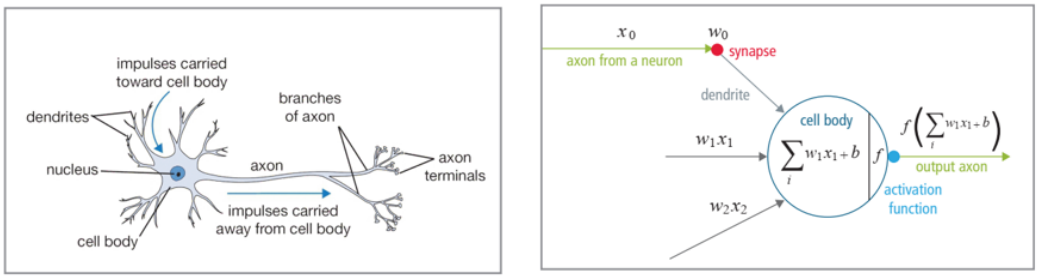


Figure 19: Illustration of a biological neuron (left) and its mathematical model (right) [49].

The ANN computational model follows a similar process to pass signals from one neuron to another. The x0 signals travel along the axons and multiplicatively interact in the point of dendrite (w0x0). Based on the synaptic strength at that synapse w0, the signal will pass with the dendrites. Synaptic weights can learn and control the strength of the influence of one neuron or another [49]. All of the dendrites carry a signal to the cell body and make a summation. The neuron fires if the final sum is above a specified threshold and sends a spike towards the axon.

Neural networks are typically organized in layers made up of several interconnected nodes. In a neural network, the information is transferred from one layer to another over connecting channels. Each neuron has a unique number called bias, and

each of the channels has an attached value called weight. The bias is added to the weighted sum of inputs and reaches the neuron, and an activation function is applied at that point. The strength of the function determines if the neuron will get activated. Only activated neuron passes information to the following layers and continues up to the second last layer. By weighing the input data evidence, each of the nodes are making simple decisions. Depending on the weighing up results from the previous layer, each of those neurons makes a more complex decision. In this way, a multi-layer network of neurons can engage in a sophisticated decision-making procedure. The last layer produces outputs for the program as in Figure 20.

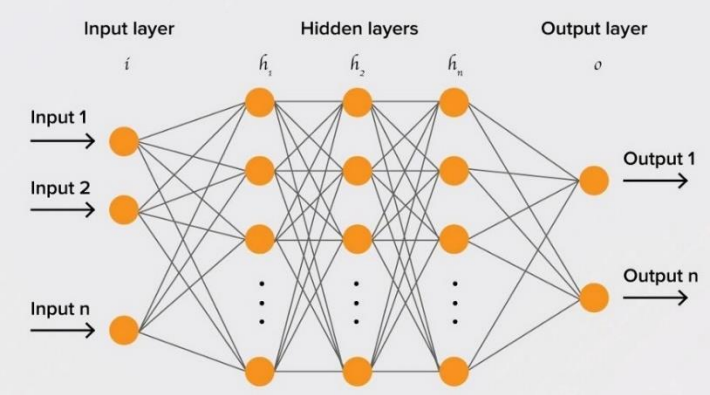


Figure 20: Neural network architectures with neurons and layers [46].

6.2 Deep Neural Network for Image Processing

There are numerous reasons to use deep learning methods such as convolutional neural networks over other traditional machine learning models. A hand-designed feature extractor gathers relevant information from the input images in the traditional method and eliminates irrelevant variabilities [33]. A particular component, such as shape, color, texture, is being considered to quantify an image [33]. The extractor is then followed by a trainable machine learner classifier such as SVM or a standard neural network that classifies feature vectors into classes as in Figure 21 [33].

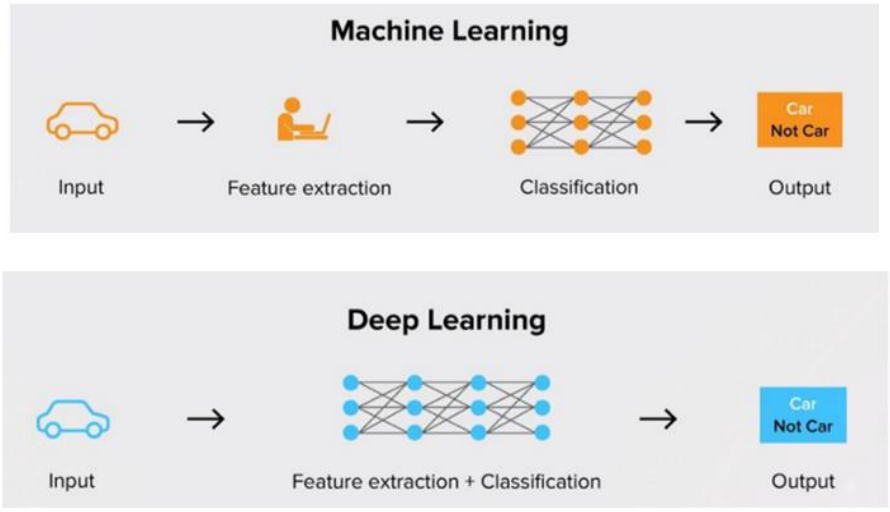


Figure 21: Up: Traditional images classification process by applying hand-designed feature extraction algorithms followed by training a machine learning classifier. Down: Deep learning approach of stacking layers that automatically learn more intricate, abstract, and discriminating features. [46]

On the contrary, CNNs are end-to-end models where convolution layers play the role of feature extractor. DCNNs structure functions in a hierarchical way to gradually pull out from low level features to most significant patterns. Neural networks scoop all the available motifs at a time and assign them random weights [54]. The network reflects importance patterns by adjusting weights during the training process. A pattern with higher weight will appear frequently and will be considered as the most useful features. The network output will provide a probability distribution within the assigned class labels, as shown in Figure 22.

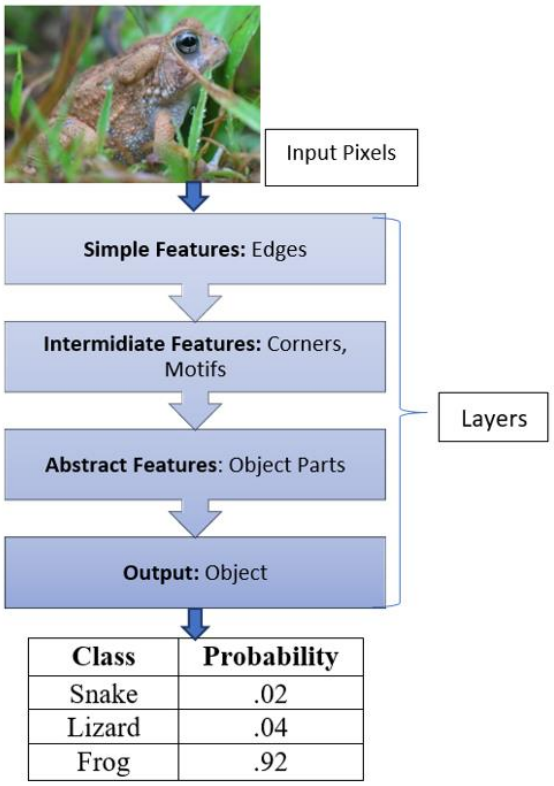


Figure 22: Stacking layers on top of each other that automatically learn more intricate, abstract, and discriminating patterns in deep learning approach.

In a CNN architecture, lower hidden layers formulates low-level structures (e.g., line segments of various shapes, orientations, edge), intermediate hidden layers combine these previous structures to model intermediate-level structures (e.g., squares, circles), and the highest hidden layers and the output layer combine these intermediate structures to model high-level structures [33].

6.3 The Architecture of Deep Convolutional Neural Network

The convolutional neural network (CNN) is a specialized type of neural network designed to do "convolution" operation of one-dimensional data, two-dimensional data, and three-dimensional image data [53]. CNN is a mathematical concept composed of three types of layers convolution, pooling, and fully connected layers. Typically, the convolution and pooling layers perform feature extraction, whereas the fully connected

layer does classification by mapping the extracted features into final output as like Figure 23 [61] [64]. This section will discuss various layers that have been used for convolution operation, CNN-1, and CNN-2.

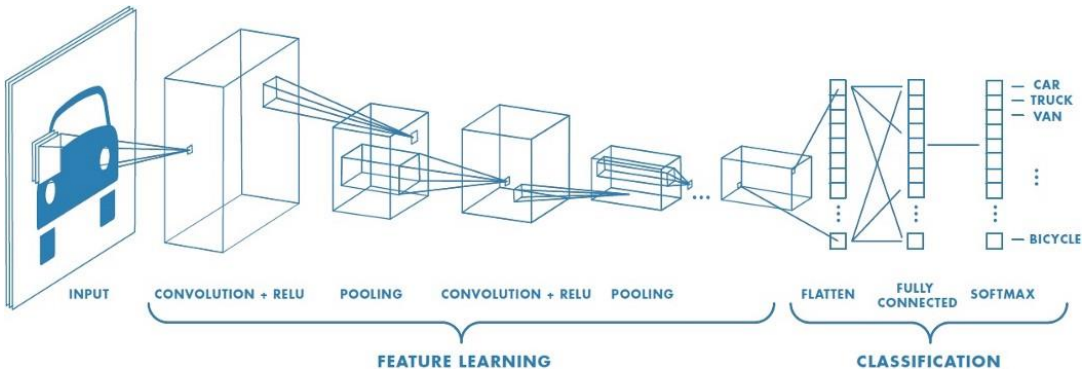


Figure 23: A CNN architecture to classify different type of vehicles using a set of layers where the convolution and pooling layers pull out patterns and the fully connected layer does classification by mapping the extracted features into final output [64].

6.3.1 Building Block of Convolution Layer

The key component of CNN architecture is the convolutional layer (CONV layer), which performs a linear operation like traditional neural networks [53]. These layers include a set of square-shaped learnable filters called “kernels” that act as feature detectors. Typically, the filters are a 3×3 matrix, but sometimes a 5×5 or a 7×7 matrix is used as a feature detector.

Each color image has three channels represented as a 3D matrix with a width, height, and depth dimension. A mathematical operation is applied to the input pixel data using the filter to produce a feature map in convolution. The operation is conducted by sliding this filter over the input matrix. At every location, an element-wise matrix multiplication occurs between the pixel value with filter size and creates a sum as a result. Next, this sum goes into the feature map, as shown in Figure 24.

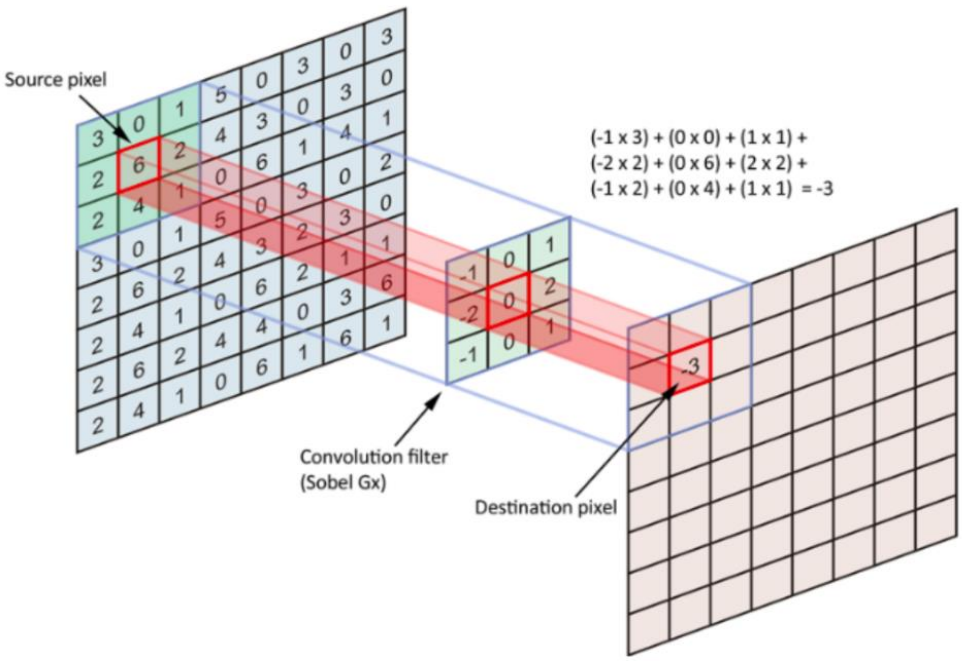


Figure 24: The mathematical operation in a convolutional layer where each filter convolves over the input volume producing stack of feature maps [64].

The above image illustrates that the kernel is getting into position at the top-left corner of the input image matrix. Then it starts moving from the left to the right, calculating the dot product and saving it to a new matrix until it has reached the last column. Next, kernel resets its position at the first column but from the 2nd-row sliding slides one row to the bottom. In that way, multiple convolutions are performed on each input, using a different filter, and resulting in a distinct feature map [64]. These feature maps are stacked together and become the final output of the convolution layer.

Three parameters control the size of an output volume: depth, stride, and padding size [33]. The depth of an output volume controls the number of neurons or filters connected to a local region of the input volume in the CONV layer [33]. As the size of feature map is always smaller than the input matrix, padding is applied to prevent the feature map from shrinking [33]. In the convolution operation, the stride denotes the number of pixels by which the filter window moves into the input matrix in each

operation. Stride decides by what step the kernel will move; for example, the stride of one makes kernel slide by one row/column at a time, and stride of two moves kernel by two rows/columns as like Figure 25.

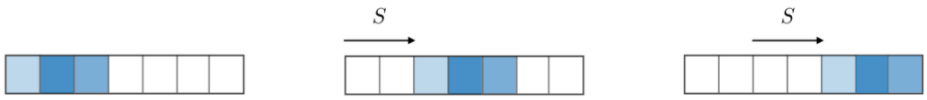


Figure 25: A movement of filters in the input matrix with a stride size is 2 [74].

Activation Function

A CNN operation relies on a non-linear "trigger" function to signal the distinctive identification of possible features on each hidden layer. In an activation layer, no parameters or weights are given to learn from images [33], rather it activates the specific type of feature at a given spatial location in the input volume. There are a variety of specific functions, such as rectified linear units (ReLUs) and continuous trigger (non-linear) functions, to efficiently implement this non-linear triggering [33]. Compared to the other non-linear functions used in CNNs (e.g., hyperbolic tangent, absolute of hyperbolic tangent, and sigmoid), the advantage of a ReLU is that the network trains many times faster. Plots of different activation functions with their corresponding mathematical function are shown in Figure 26.

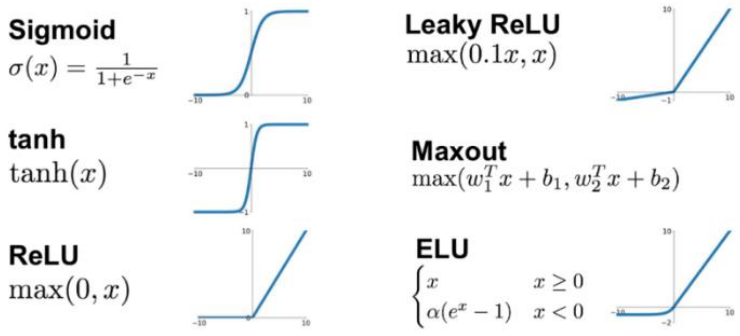


Figure 26. Plots of different activation functions with their computation behavior [65]

Pooling Layers

The pooling/subsampling layer reduces the features' resolution by progressively shrinking the spatial size of the input volume [61]. In that way, pulling operation reduces the number of parameters and computational complexity in the network [33]. Moreover, it helps to control overfitting [33] and makes the features robust against noise and distortion [51]. There are two ways to do pooling: max pooling and average pooling. As seen in Figure 27, the reduction in input size depends on the pooling layer's size and stride.

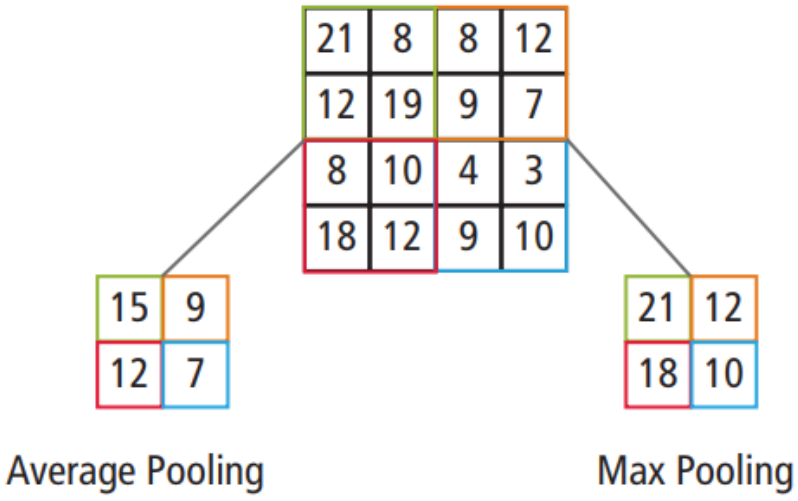


Figure 27. Pictorial representation of max pooling and average pooling [51]

Batch Normalization

Batch Normalization is a technique for training a very deep neural network by adjusting and scaling the input layer's activations for each mini batch [66]. This layer normalizes the distribution of features coming out of a CONV layer [33]. Using batch normalization shows several benefits to the model, such as effectively reducing the number of epochs while training time by making the learning rate and regularization less volatile to the model. Moreover, Batch normalization layers help to make a stable

training process that allows a large variety of learning rates and regularization strengths in the model [33]. Furthermore, a more stable loss curve can be noticed by introducing batch normalization in the networks

Fully Connected Layer

The output of both convolution and pooling layers are 3D volumes. The final convolution or pooling layer's output feature maps are typically flattened and transformed into a one-dimensional (1D) array of the vector [61]. The flatten output vectors becomes the input to a dense layer, denoted as a fully connected layer. Fully connected layers are often used as the final layers of a CNN. This layer mathematically sums the weight of the previous layer of features to determine a specific output result [51].

6.4 Regularization Methods

A common struggle working with a small dataset is that the neural network performs incredibly well on the training set but not nearly as good on the test set. This is a sign of overfitting where the model cannot generalize well to the unknown samples. Adding more data is a solution that is quite unobtainable for real-world dataset. In that case, regularization is a standard method to reduce overfitting and improve the model's performance. It ensures a balanced training and testing performance by controlling model capacity [33]. Among several regularization options, this section includes those techniques that have been used in the experiment of this research work.

Dropout Layer

A Dropout is a regularization technique that aims to prevent overfitting by increasing testing accuracy [33]. While training a model, dropout layers randomly disconnect inputs from the preceding layer to the next layer for each mini batch set in the

network architecture [33]. A neuron is temporarily disabled in each iteration by setting a dropout value with a probability p [33]. The hyperparameter p is the dropout rate that can initiate a number (e.g., 0.3 as 30% p-value) in the code. To activate the dropped-out neurons alternatively at every training step, the dropped-out neurons are resampled with probability p as in Figure 28.

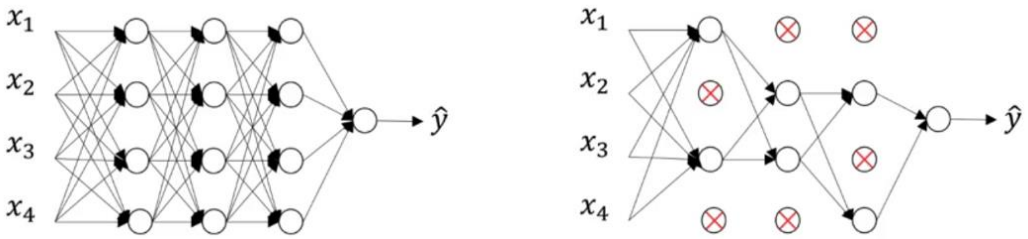


Figure 28. Pictorial representation of drop out layers [69].

Early Stopping

A callback function monitors the model's performance for a given set of operations or a given number of epochs [68]. After a certain number of iterations, the model might start to overfit the training data. This function halts the training process when the model stops improving its accuracy and restores the best weights after stopping the training as in Figure 29 [68].

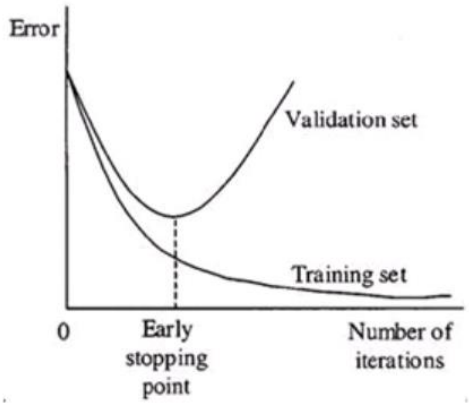


Figure 29. Early stopping breaks the training procedure after reaching a particular accuracy/loss score [60]

7. METHODOLOGY

7.1 Data Preprocessing

7.1.1 Cleaning and Scaling

It is essential to prepare data before applying towards a machine learning model to make the computation efficient. The neural network model requires careful consideration of the input data, especially for images, as the dataset differs in resolution, scale, and format. For this research work, preprocessing has been started with examining and standardizing the dataset. As the online dataset accumulated from various sources, a careful inspection was needed to remove unrepresentative data such as graphics and animation. On the other hand, camera trap data was required to scrutinize to confirm that each image contains the target species.

One crucial preprocessing step for CNN architecture is to resize all the images in the dataset to a unified dimension: identical widths and heights. The scaling process needs to maintain the aspect ratio of images to avoid compression and distortion [33]. The samples have been resized and scaled appropriately by providing the instructions in the script.

7.1.2 Oversampling

Real-world data often endure class imbalance where samples from one class or multi classes are overrepresented in a dataset. Class imbalance influences biasness towards the heavily represented categories among the classes [33]. The popular strategies for dealing with the class imbalance is up-sampling the minority class, down-sampling the majority class, and generating synthetic training samples [56]. Down-sampling randomly removes data from sufficient observations to establish a comparative ratio of

classes with significant data [57]. On the other hand, oversampling creates copies of samples of the minority class to maintain the same number of data distribution as the majority class [57].

For the online dataset, samples of each group have been collected carefully to avoid data imbalance. However, the camera trap dataset suffers from class imbalance with 700 snake images, 600 toad images, and 1,800 lizard images. As the project deals with a small camera trap dataset, the oversampling technique has been applied to equalize the sample size of all the classes. The sample selection differs for CNN-1 and CNN-2 due to the algorithmic behavior and data specifications. Additionally, the data count for a binary problem (e.g., snake vs. background) is different from a multiclass problem (e.g., all three classes). According to the experiment requirement for CNN-1 and CNN-2, the number of snake and toad samples were increased by rotating 180-degree angles of the original images. Figure 30 shows how snake and toad samples were enhanced for the multiclass classification computation-

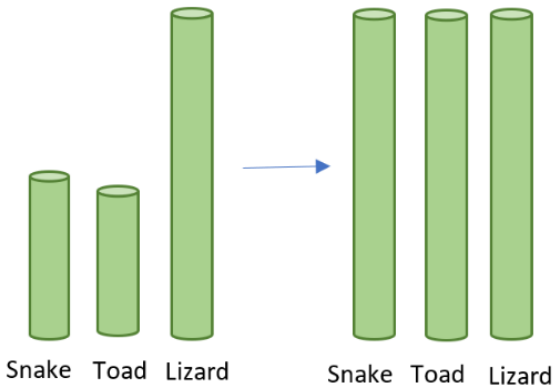


Figure 30: An illustration of balancing samples of all species by oversampling snake and toad images. Oversampling has been done using data augmentation by180 degree angle rotation.

7.1.3 Augmentation

The image augmentation technique creates data variations synthetically in existing images to represent a comprehensive set of possible changes [58]. Augmentation will provide the model a wide range of transformation so that the model learns objects in various forms and shapes in the training phase [58,59]. This technique also helps to increase the model's generalization ability to predict an unseen image of target classes. Moreover, in some cases, augmentation helps to reduce the overfitting problem [58,59].

Data augmentation can be applied as a pre-processing step in two options: *dataset generation* and enlarging an existing dataset, and on-the-fly data augmentation [59]. The difference between the two methods relies on the data enlargement procedure and the implementation time. The dataset generation is an additive process to expand the existing dataset whereas, on-the-fly data augmentation using Keras ImageDataGenerator does not combine the transformed data into the original dataset. It just performed with the modified data while training time.

To achieve a relative class balance and to improve the generalization ability of a model, both the augmentation actions have been applied in the thesis work. Although, on-the-fly data augmentation has been introduced only in CNN-2, which distinguish the computation behavior between two models. Below subsections describe two augmentation process elaborately.

Data generation: In this method, the dataset is expanded by adding slightly transformed samples to the existing directory. This is an offline process that is usually applied for a small dataset. The steps are –

- Loading the original input image from the folder.
- Applying random transformation in the original images such as rotation, cropping.
- Adding the transformed image in the existing dataset.

For this project, offline augmentation has been employed in the oversampling phase to balance the same number of examples of all three species. As mentioned in the oversampling section, this is accomplished by applying the 180-degree phase shift rotation of the original images and then adding together in the directory. Both CNN-1 and CNN-2 have operated with the expanded dataset.

***On-the-fly data augmentation using Keras ImageDataGenerator*:**

The CNN-2 utilizes this augmentation technique in the training phase by using Keras ImageDataGenerator. This is an online or real-time augmentation where transformations occur in the training session as in Figure 31. This process ensures that the network sees a new set of samples with slight variations at every epoch while training the model. This is done by applying different transformation techniques like zooming, shearing, and rotating the existing image by a few degrees. The process follows the following steps-

- Presenting an input batch of images to the ImageDataGenerator.
- Transforming each image in the batch by a series of random translations, rotations, and other types of transformation.
- Replacing the original batch with the new, randomly transformed batch.
- Training the CNN on this randomly transformed batch.

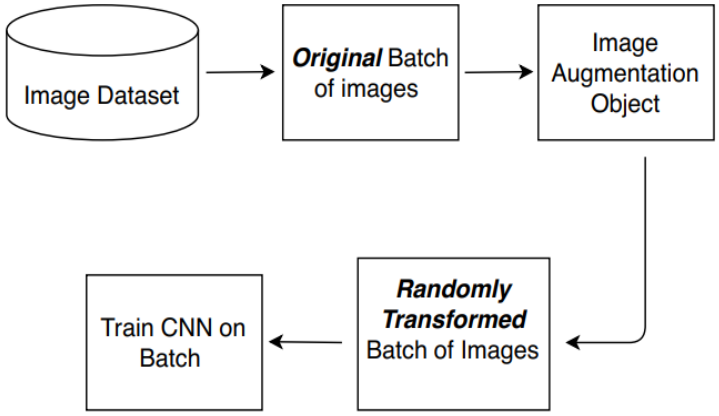


Figure 31: On-the-fly augmentation process in CNN-2 using image batch manipulations [59]. This process configures random transformations of samples during training time by using keras ImageDataGenerator.

Data augmentation implementation using keras

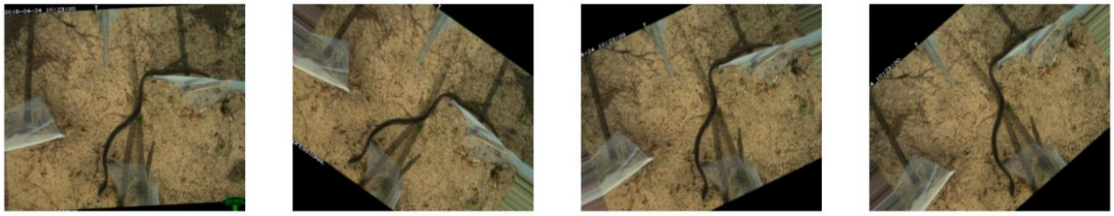
Augmentation parameters and range have been selected keeping in mind the complexity of target species size, shape, and image quality, such as the brightness level**.** It has been noticed that snake and lizard can appear in corners of an image, where toad has been mostly seen near the background. That is why snake and lizard images have given 30% zoom range, while toad images have 70% shown in Table 3. Moreover, only toad images have tuned with brightness alteration options as most of the toad images are night vision images having black and white pixel intensity. Table 3 summarizes parameters and ranges of augmentations that has been applied for different species.

Table 3: Several augmentation techniques used in CNN-2 model using Keras ImageDataGenerator.

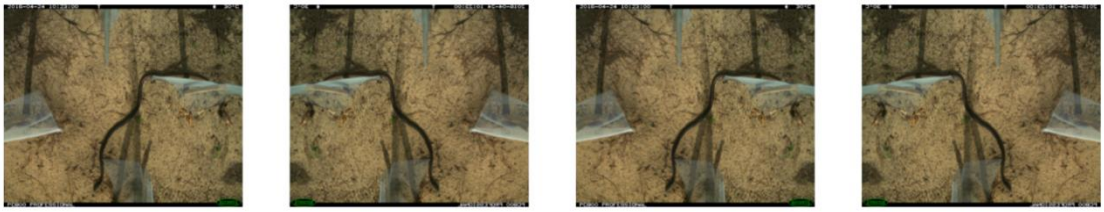
Augmentation Techniques	**Parameters and Range**	**Applied for species**
Rotation	40 Degree	Snake, Toad, Lizard
Flipping	0.2	Snake, Toad, Lizard
Shearing	30	Snake, Toad, Lizard
Shift horizontal	TRUE	Snake, Toad, Lizard
Zoom in	0.3	Snake & Lizard
	0.7	Toad
Changing brightness or contrast (by changing height, width, and color channel dimensions)	100	Toad

Example of several augmentation techniques is represented in Figure 32.

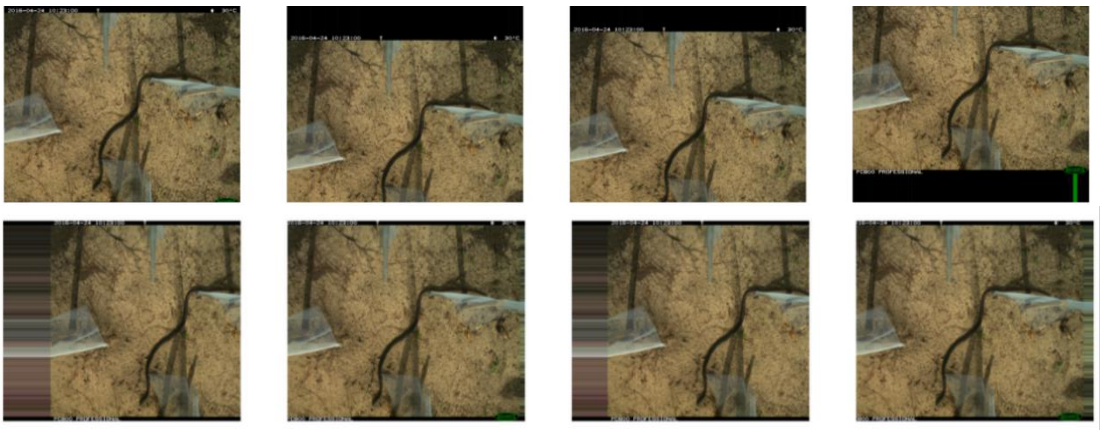
- **Rotation**: Rotation range: 40 degree



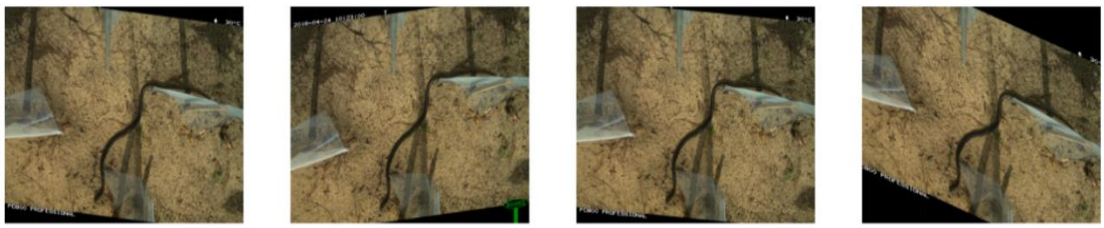
- **Flipping**: Horizontal



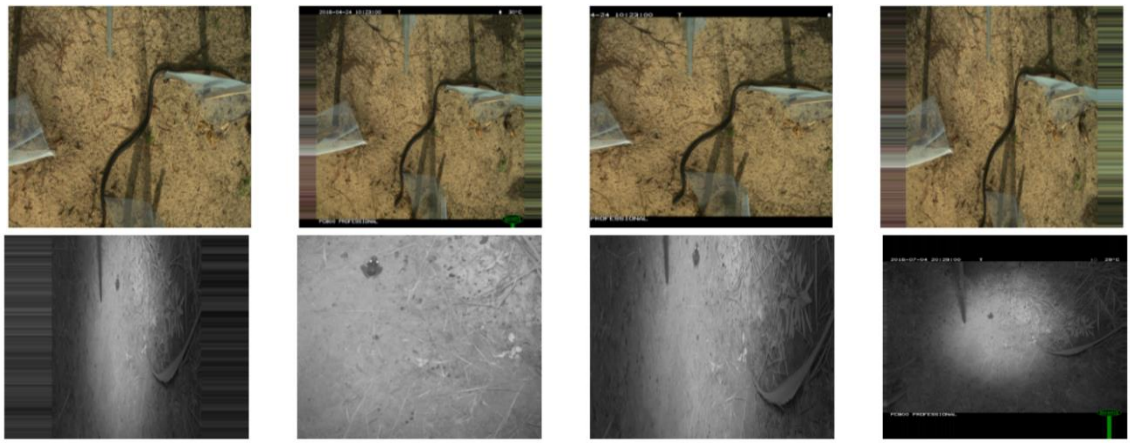
- **Shift:** Height and width



- **Shearing**: Shearing transformation is shifting one part of the image like a parallelogram; fixing one axis and stretching the image in a certain angle [63]. Shear range=30



- **Zoom in:** Zoom range for snake and lizard = 0.3, for toad = 0.7



- **Changing brightness or contrast:** The color brightness was altered by changing the value of color channel. This technique has been applied only to the toad images.

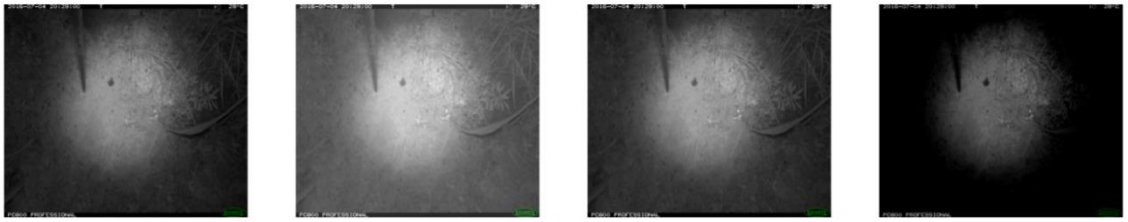


Figure 32: Several augmentation examples applied in CNN-2 to transform images in training phase.

7.1.4 Data Partitioning

The DCNN models estimate the statistical trends in the data, such as the features in an image. Therefore, it is essential to follow a similar statistical allocation for training and evaluation purposes [62]. The network learns relevant features in the training session and is monitored on the validation part to reduce overfitting problem. Afterward, the model is tested on an entirely separate set of samples from the overall dataset that the model did not use during the training or validation phase.

While dividing samples, it has been ensured that the split was developed randomly and was not overlapped with each other. Otherwise, using the testing samples as part of training data might take an unfair advantage as it has already learned sample characteristics while training [33]. A separate set of test data was kept aside for each target species that have been utilized in both phases (online and camera trap data), and for both models (CNN-1 and CNN-2). The rest of the samples were divided into training and validation set.

Training and validation data separation for CNN-1 and CNN-2 differs from their distinct data loading framework. In CNN-1, training and validation data are in the same directory, and they are divided randomly in the code as per given instruction (e.g., 70/30 or 80/20). On the other hand, in CNN-2, training and validation data partitioning was done manually, and data is loaded separately from two distinct directories. Table 4, 5 and 6 listed the sample partitioning quantity for both models for both datasets.

Table 4: Balanced dataset partitioning of online images

Online data splitting	**CNN-1**		**CNN- 2**		
	Train & Validation	Test	Train	Validation	Test
Snake	4,000	500	3,000	1000	500
Toad	4,000	500	3,000	1000	500
Lizard	4,000	500	3,000	1000	500

Table 5: Balanced dataset partitioning for CNN-1 of camera trap images

Camera-trap data splitting for CNN-1 (without augmentation)							
	Snake vs Background		Toad vs Background		Lizard vs Background		Snake vs lizard vs toad vs Background
	Snake	Background	Toad	Background	Lizard	Background	All four class
Train & Validation	1300	1300	1300	1300	1700	1700	1700 of each species
Test	100	100	100	100	100	100	100 of each species

Table 6: Balanced dataset partitioning for CNN-2 of camera trap images

Camera-trap data splitting for CNN-2 (with augmentation)							
	Snake vs Background		Toad vs Background		Lizard vs Background		Snake vs lizard vs toad vs Background
	Snake	Background	Toad	Background	Lizard	Background	All four class
Train	2,500	2,500	1,000	1,000	1,450	1,450	1350 of each species
Validation	500	500	300	300	350	350	350 of each species
Test	100	100	100	100	100	100	100 of each species

7.2 CNN Model Configuration

In the current study, two self-trained CNN frameworks named CNN-1 and CNN-2 have been developed and tested considering the amount of available training data and the data quality. First, the CNN-1 has been constructed and trained for both datasets (online and camera trap data). CNN-2 has been established by introducing several data augmentation processes to optimize the performance, as discussed in section 7.1.3 in the preprocessing stage. As mentioned before, the sequential convolutional part of CNN algorithm is the same for both of the models. However, substantial differences have been noticed by implanting the data augmentation process in CNN-2, especially in the experiment of camera trap data.

The purpose of applying two separate models is to explore the influence of the augmentation technique in the camera trap dataset and compare the performance to pursuit a better recognition solution. Figure 33 portrays an overall recognition structure that has been followed while designing the CNN model.

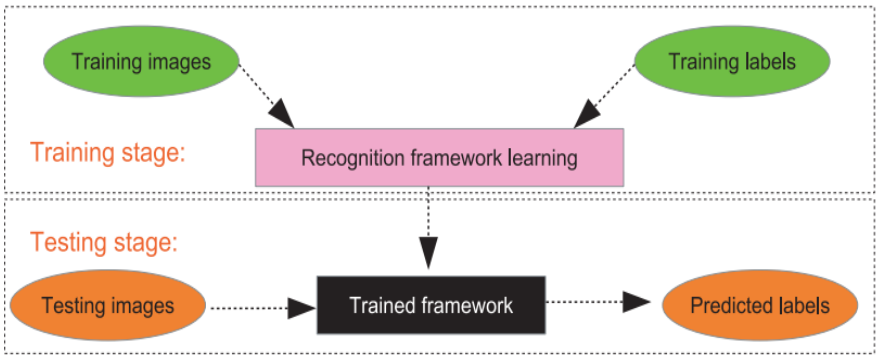


Figure 33: An overall concept of training and testing processes of a DCNN recognition framework [38]

The architecture of the CNN network is composed of assembling a sequence of several Convolutional layers (CONV) and subsampling layers (Batch Normalization, Activation, Pooling, and Dropout), followed by Fully Connected (FC) layers at the end.

The CONV layer is the core building block of CNN, consisting of learnable filters that extract local features from images. Batch Normalization *(BN)* layers are also included after every CONV layer, which will normalize each training mini-batch by using higher learning rates [33] to improve accuracy and speed up the training process [34]. Every BN layer is followed by an Activation layer ReLU to introduce non-linearity, which will allow the architecture to learn complex relationships in the data. Next to the Activation layer, Max pooling *(Max Pool)* layers are added to compress or generalize feature representations by taking the maximum of the input values. After that, Dropout layers are incorporated to reduce overfitting and improve generalization in deep neural networks [23]. The 2D images are flattened into a one-dimensional vector for the convenience of a Fully Connected layer. In the end, two Dense layers have been added along with the Dropout layer and sigmoid activation function. Below Figure 34 depicts a CNN model configuration.

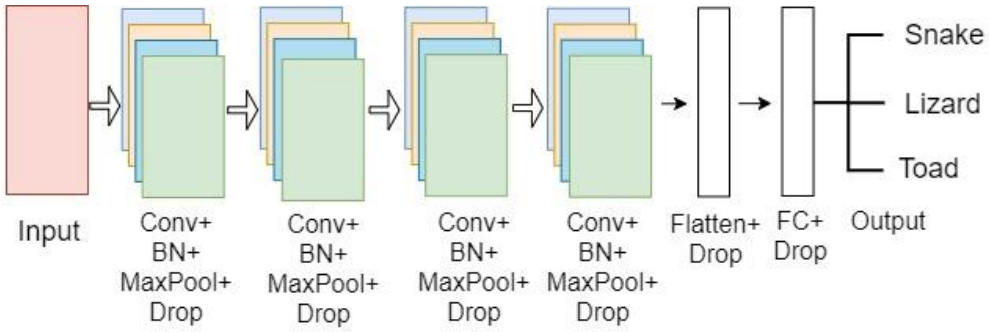


Figure 34: An example of four layers CONV architecture for snake, lizard, and toad classification.

Before confirming the final CNN model, different model parameters have changed in each experiment, and the subsequent result has then compared to obtain a high performing model accuracy value. Architecture of phase one differs with number of

layers and parameters as it compute with more data than phase two. Model design for phase one and phase two are described in the following sections.

7.2.1 Model Architecture for Phase One (Online Dataset)

Phase one aims at dealing with high-resolution target species images collected from various online sources. Two CNN architectures with different depths are employed to solve a binary and multiclass problem. At first, a set of four 2-D convolutional layers with subsequent Batch Normalization, Activation, Pooling, and Dropout layers has been built to run a binary problem with 9,000 images. Later on, the model was modified with more filters and fine-tuned parameters to add enough complexity to the architecture to train 13,500 images of three classes of species. A list of parameters and hyperparameters in of CNN architecture for the online dataset are presented below-

- *CNN layers:* 4 set of convolution layer- *Convolution>>BN>>Activation>>Pooling >>Dropout* layers, respectively.
- *CNN layer depth:* The number of filters of first two layers are 32, and rest two layers are 64. For the multi-classification CNN architecture, the first two layers have 32 filters, third layer has 64, and the fourth layer has 128 filters.
- *Filter size:* All the convolution layers have a kernel size of 3×3, and all the Pooling layers have a pool size of 2×2.
- *Stride and padding:* Stride was kept at the default value 1, and padding size was chosen valid padding for the final architecture.
- *Dense layer:* Dense layer filter size is set at 128 and 512 for the binary model and the multiclass model consecutively.

- *Activation function:* Each convolutional layer is associated with the ReLU activation function right after the BN layer.

For output layer, CNN-1 uses sigmoid and softmax function for the binary model and the multiclass model consecutively. For CNN-2, SoftMax has been used for both binary model and the multiclass model.

- *Dropout layer:* 50% dropout probability showed considerable results for the convolutional neural network.
- *Initializer:* Each layer is initialized with *glorot_uniform*.

7.2.2 Model Architecture for Phase Two (Camera Trap Dataset)

While designing and evaluating automatic classification for camera trap images, two different scenarios were considered:

(a) Binary classification to identify a target class (snake, or lizard, or toad) with respect to the background image.

(b) Multi-classification to distinguish three animal species with respect to the background image.

Such planning is that three of the class images have a distinct attribute within the background, and snakes get an advantage due to larger body shape than lizards and toad. Background images have been considered a standard reference to construct binary and multiclass classification frameworks to avoid any impartiality within the classes. A list of parameters and hyperparameters of CNN-1 and CNN-2 for the camera trap dataset are given below-

- *CNN layers:* 3 set of convolution layer- *Convolution >> BN>Activation>>Pooling >>Dropout* layers respectively

- *CNN layer depth:* For the binary and multiclass problem, the number of filters of first two layers is 32, and the third layers are 64.
- *Filter size*: All the convolution layers have a kernel size of 3×3, and all the Pooling layers have a pool size of 2×2.
- *Stride and padding:* Stride was kept at the default value 1, and padding size was chosen valid-padding for the final architecture.
- *Dense layer:* Dense layer filter size is set at 64 for the binary model and 128 for the multiclass CNN consecutively.
- *Activation function:* Similar to the phase one, each set of CONV layers is associated with the ReLU activation function.

  For output layer, CNN-1 uses sigmoid and softmax function for the binary model and the multiclass model consecutively. For CNN-2, the class mode has been chosen 'Categorical' as an autoencoder in the script for one-hot encoded labeling, which returns a 2D one-hot encoded labels of the classes instead of their class name [71]. SoftMax has been used for both binary model and the multiclass model.
- *Dropout layer:* CNN-1 utilized 25% dropout probability, CNN-2 was incorporated with 50% dropout value.
- *Initializer:* Each layer is initialized with *glorot_uniform*.

7.3 Optimizing the CNN Model

As deep learning is an iterative process, various parameters can be adjusted to enhance the training speed and efficiency of learning procedure. Some parameters can be tuned, for instance, epochs, learning rate, batch size, and Dropout value to improve CNN model performance. For this research work, much experiment has been done to determine the suitable parameters to measure accuracy, or to obtain a reasonable learning curve. In this section, the most impactful hyperparameters are discussed that have been utilized throughout the experiments.

Batch size

The given batch size selects a set of samples from the training dataset to work through before the internal parameters of a model are updated [72]. Mini-batch training reduces training time and makes convergence faster. The batch size ranged from 32, 64 and 128 was tested in the mzodel where the best result was provided by a batch value 32.

Number of epochs

The number of times the entire training set pass through the neural network is denoted as the number of epochs [72]. A CNN model usually runs until the validation error become very close to the training error. Working with online images, the model had to run up to 250 epochs to get convergence due to data size volume. As the sample size of camera trap project is small, the network was run for 100 epochs.

Learning rate

The learning rate is a crucial hyperparameter to tune the neural network, which controls how much the optimization algorithm's weight will be updated [65]. For all experiments, learning rate with 0.01, 0.001 and 0.0001 have been tested. The best result

for online and CNN-2 was achieved with a keras default learning rate of 0.01 and for CNN-1 experiment, the learning rate was 0.0001.

Dropout for regularization

In order to battle with overfitting, Dropout values were also tuned after each Convolution and Fully Connected layer. For online images, the dropout value was kept 0.5 for all the layers. For the experiment of camera trap images with CNN-1 model, the best accuracy was achieved with a dropout value of 0.25 after the Convolutional layers and a 0.5 dropout value after the Fully Connected layer. The learning curve of CNN-2 experiments were suffering from overfitting problem, the dropout value was kept at 0.5 for all the layers.

7.4 Computational Tools and Environment

For this project's writing script, the Python programming language was utilized using deep learning libraries such as Keras, Numpy, Scikit-learn, and Matplotlib. Python is a flexible, intuitive syntax [33] that allows developers to build, test, and tweak a model efficiently. Essential image processing operations such as loading images from disk and displaying them to our screen were performed with OpenCV standard library.

After building the initial architecture, the model was run multiple times in the LEAP cluster, a high-performance computing cluster facilitated by Texas State University. LEAP stands for “Learning, Exploration, Analysis, and Processing,” which is configured with 28 CPU cores, Dual 2.4 GHz E5- 2680v4 Intel Xeon (Broadwell) processors, 15 TBs of memory, and 48 TBs of local storage in total [73]. High throughput analysis was achieved using the cluster by submitting parallel jobs to evaluate the optimized hyperparameters.

8. EXPERIMENT AND RESULT ANALYSIS

8.1. Experiment and Result Analysis for Phase One (Online Dataset)

Though the goal of the research work is to recognize wild animal species from a large camera trap dataset, the initial work started with building and training a CNN classifier with online images. The aim was to create a binary and multiclass recognition system prototype for future implementation using real-world datasets. The initial work helped to get familiarized with the concept of classification using DCNN and understand computer vision analysis with image data. Once the model was constructed, it has been utilized for the camera trap data, where the previous models were fine-tuned according to the desired output.

A binary and a multiclass structure were experimented with two CNN models with 4,500 online images of each group (snake, lizard, and toad). As an example of a binary recognition problem, a model has been developed with toad and snake species. Later, the work was extended by adding lizard as a class. The experiment results were compared within the group of species and also between the models (CNN-1 and CNN-2 architectures) as described in below subsections.

A) Binary Classification Result (Toad And Snake)

In the initial stage, the research work started with building a binary classification model (CNN-1) of snake and toad with 414 images of each species from the Caltech dataset. The model was composed of CONV layers with activation ReLU function, 2x2 MAX Pooling layers, added with Dropout layers. The model got overfitted after 30 epochs due to the limited imagery samples (828 total images). The best training and validation accuracy of that CNN-1 model was 67% and 60%, respectively [70].

A reasonable extension of that binary experiment has been conducted to improve the performance by adding more images into the dataset. The model is trained and validated with a balanced two-class image dataset consisting of 8,000 images where 70% of data has been utilized for training, 30% is for validation. A separate sample set of 1,000 images has been utilized for testing purpose. The input data sizes varied in different resolutions in the RGB channel, but images were scaled down to 100 pixels in greyscale to reduce computational time and complicacy.

Many changes have made in the architecture, such as changing layers, filter count, drop out value, and other parameters to the previous model considering the data size. Also, a Batch normalization layer and initializer were introduced to the model.

The below training and validation loss and accuracy curves in Figure 1 illustrate the learning performance changes over time. As expected, the validation curve decreases, followed by the training curve for 200 iterations. Both the training and validation loss decreases with a minimal gap between the two final loss values indicating a fitted model. Both curves have fluctuation because the model is changing its prediction as plotted in

Figure 35. The average training accuracy of the CNN-1 model is 79%, and the average testing accuracy score for this model was 76%.

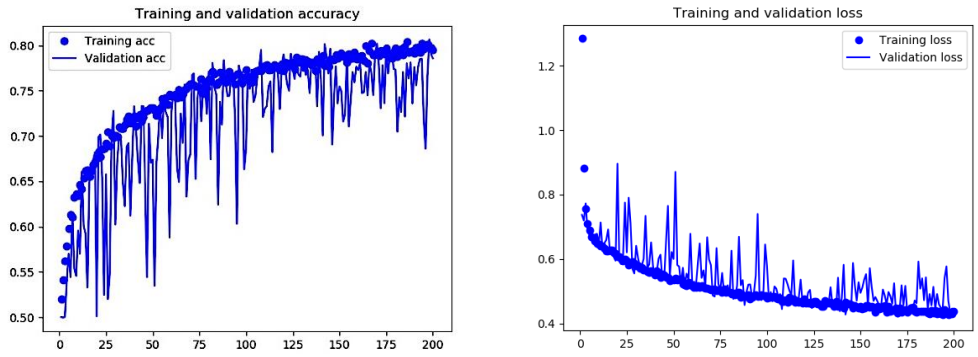


Figure 35: The accuracy and loss curves (training and validation) during the 200-epoch training process for the final CNN-1 model.

A reasonable improved can be noticed in CNN-2 by incorporating several data augmentation in techniques explained in section 7.1.3. With the same sequential model configuration, the outcomes were enhanced, having an 83.21% accuracy for training, and an 82% accuracy validation accuracy shown in Figure 36.

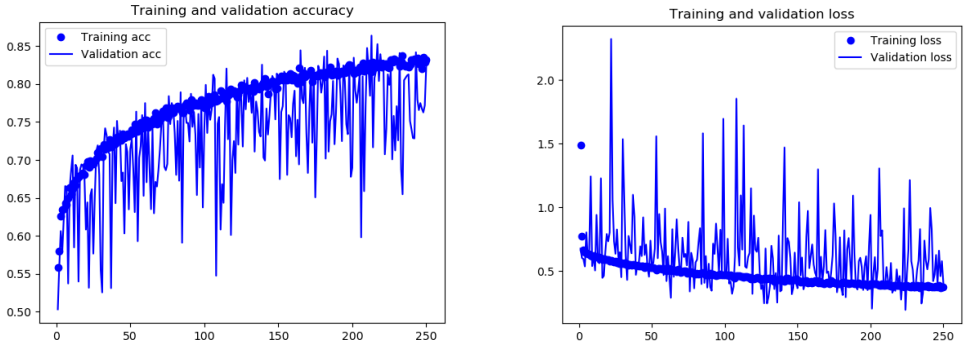


Figure 36: The accuracy and loss curves (training and validation) during the 250-epoch training process for the final CNN-2 model.

The below Figure 37 (a) and (b) confusion matrices are among the average outcomes of several computations of the final CNN-1 and CNN-2 models consecutively.

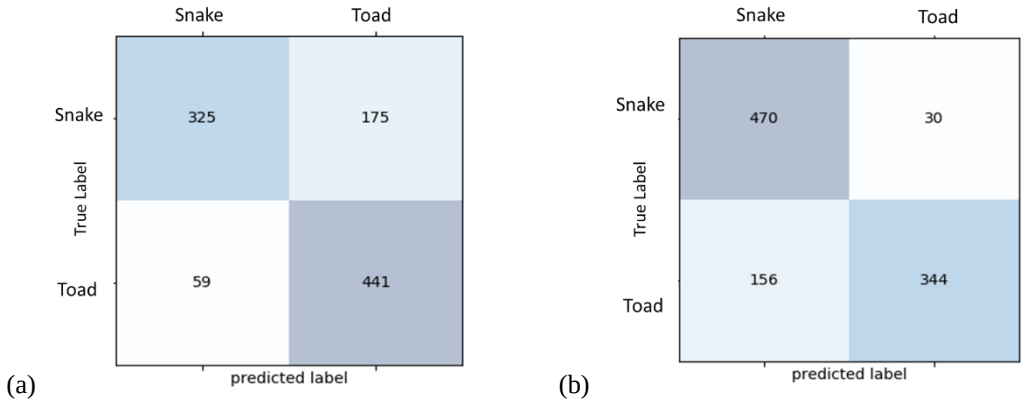


Figure 37: Confusion matrix of Snake vs. Toad experiment (a) for CNN-1 and (b) for CNN-2.

The confusion matrix in Figure 37 (a) has a 76% overall testing accuracy, where 176 snake images were misclassified as a toad, and 59 toads were misclassified as a snake. Figure 37 (a) has an overall 81.4% accuracy where 30 snakes were misclassified as a toad, and 156 toads were misclassified as a snake. Both confusion matrices confirm that data augmentation was able to increase the prediction ability for separate testing data for a binary problem.

B) Multiclass Classification Results of Toad, Lizard, And Snake

For the multi-classification model, the model is trained with three herpetofauna groups of species, snake, toad, and lizard, which eventually lead to add more data into the model: 12,000 samples for training and validation and 1,500 for testing. To make the CNN classifier enough compatible to extract features from individual class, the model has modified by adding more filters into the fourth layer. Moreover, the model showed a better performance by decreasing the neurons in the dense layer. However, the model's performance is lower for multiclassification than the binary problem as plotted in Figure 38 and 39.

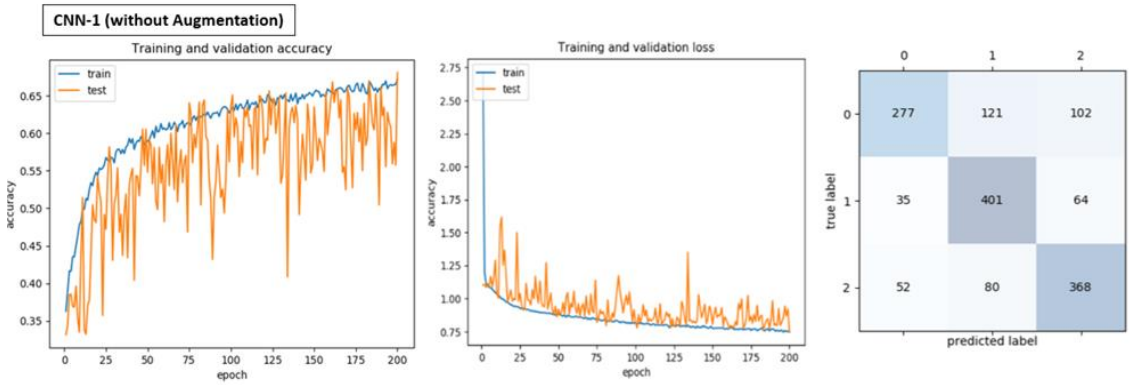


Figure 38: The accuracy, loss curves (training and validation), and confusion matrix of CNN-1 model for snake, toad and lizard classification. Here "Snake =0", "Toad =1" and “lizard=2”.

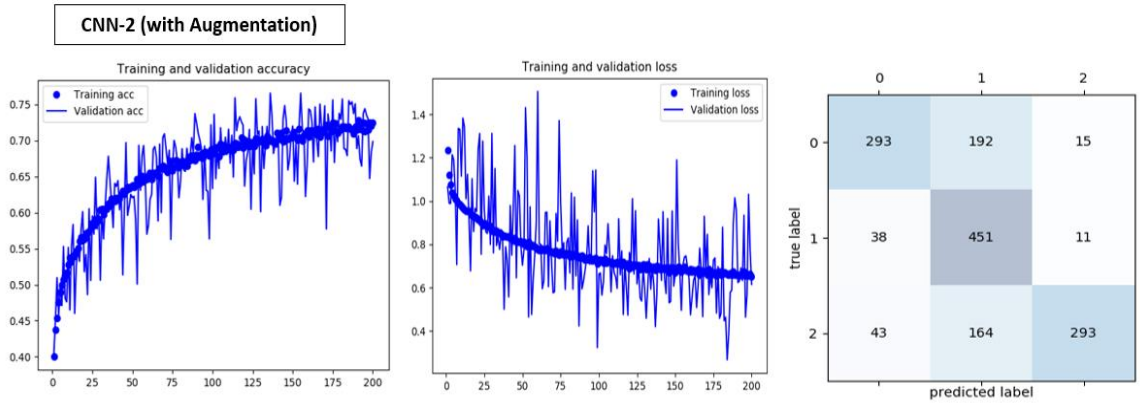


Figure 39: The accuracy, loss curves (training and validation), and confusion matrix of CNN-2 model for snake, toad and lizard classification. Here "Snake=0”, "Toad =1" and “Lizard=2”.

The multi-classification results yielded lower accuracy than a binary problem achieving a 66.41% training, 56.15% validation and 69.73 % testing accuracy for CNN-1. CNN-2 scored slightly higher than CNN-1 with an accuracy value 7of 2.44%, 69.85%, and 69.13% for training, validation, and testing, respectively. Even the confusion matrix shows that the model had difficulty recognizing species properly between three classes. A lot of snake and lizard samples are misclassified with toad. The models predicted toad quite well among three of the species though the performance for snake was worst. The below Table 7 represents the overall classification result of CNN-1 and CNN-2 models for online dataset.

Table 7: The overall classification result of CNN-1 and CNN-2 models for online dataset.

	Snake vs Toad (Accuracy in percentage)				**Snake Vs lizard vs Toad (Accuracy in percentage)**		
	Training	validation	Testing		Training	validation	Testing
CNN-1 (without Augmentation)	79	76	76.6		67.18	68.08	69.73
CNN-2 (with Augmentation)	83.21	82	81.4%		72.44	69.85	69.13

From the above table, it can be summarized two outcomes- (a) CNN-2 proved an improvement in the result for binary and multiclass recognition problem, (b) the overall accuracy declined for multiclass recognition problem than a binary problem.

While experimenting a multi-classification model, it has been noticed that the added class brings more complications within the network due to the additional characteristics of the new samples. As seen in section VII, the samples of three species have their attributes such as dynamic object position, light illumination, occlusion, and complicated animal poses, making the classification process challenging. Moreover, three species have inter-class similarities, especially for partially body shape, as described in the dataset chapter, which creates extra difficulty to label them in the testing phase. Furthermore, the model takes more time to finish computation and have more memory requirement

8.2. Experiment and Result Analysis for Phase Two (Camera Trap Dataset)

The experiment analysis of online dataset demonstrates that both CNN-1 and CNN-2 models are well developed for recognizing animal species with reasonable accuracy. Nevertheless, with the same models, real-world images have shown performance deviation since the camera trap examples are unmodified and naturally occurred from the environment. Not only that, both models, CNN-2 and CNN-2 performed differently providing a different set of results. However, this section is dedicated to highlight and discuss the essential experiments and corresponding result analysis of camera trap species classification.

Three vital concern have been considered while developing the classification algorithm with camera trap data-

1. Though the camera trap produces a large amount of dataset, there are very few target species images to train a model.
2. Dataset was unbalance for three target species (snake =700, toad=600, lizard=1,800).
3. Among three species, the snake has a decent body size, while toad and lizard pose a minimal pixelated area in the background.

First and second challenges have been addressed by incorporating preprocessing techniques to a dataset such as oversampling images to balance the dataset and augmentation technique to boost the model's generalization ability, as explained in chapter VII. Moreover, models have been fine-tuned with various hyperparameters in the algorithm throughout the experiment.

All three species have been classified individually regarding background images producing three separate binary problems; ‘lizard vs. background,’ ‘toad vs. background,’ and ‘snake vs. background’ to find a logical solution of third concern. Background samples can be referred to as images that do not contain any of the three target species in that data point. A new label of dataset named ‘background’ has been formed from camera trap images with the same resolution and environment condition as the other data examples. In the end, all four sets of labeled data have experimented together CNN-1 and CNN-2, and results were compared for a better understanding of recognition performance.

A model’s performance can be evaluated on how the classifier will recognize new or unseen data from the same distribution of samples used to train the model. This can also be defined as the generalization ability of a CNN classifier. For camera trap images, after training the model, the performance has been validated with a given set of samples that measure how well the model is generalizing the trained class. The classification evaluation was done with a separate set of the testing dataset. The test result has been used to plot a confusion matrix that summarizes the prediction of classification results, including correct and incorrect label estimation.

Along with the learning curve and confusion matrix, the model will predict an unseen image from the saved model. After training, the model was saved using *Keras* function model.Save, where the saved model will store the weights and architecture in separate files. Utilizing the load_model function, the model is directly used to predict a new image that the model has never faced in training and testing. For that testing purpose, a completely isolated set of samples of 10 images of each species has been

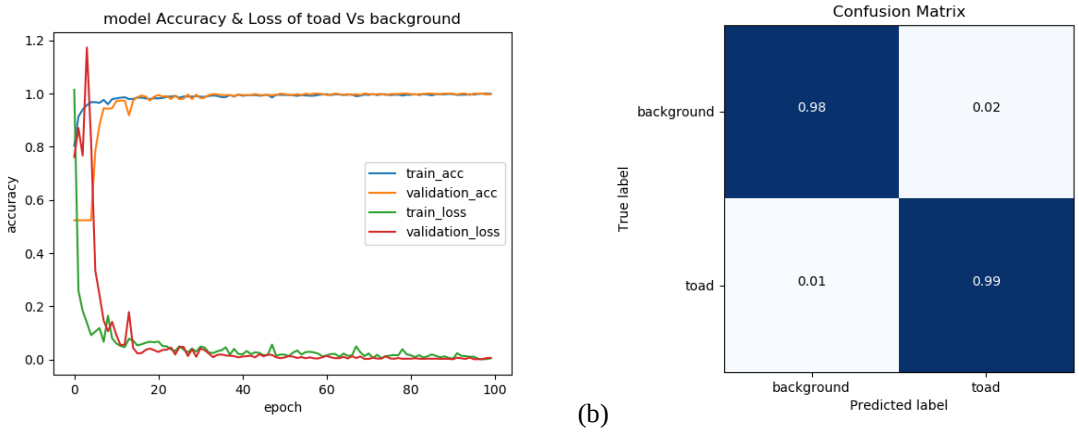
separated and later applied to test the model's generalization ability. The subsequent sections will describe the result analysis of CNN-1 and CNN-2 separately.

8.2.1 Performance Evaluation of CNN-1 (Without Augmentation)

In CNN-1, training and validation samples were loaded together from the same directory and split randomly by instruction in the algorithm. Due to the small sample size of 1,300 for training and validation of each species, 80% was used to train the model, and 20% for validation of the training. The input size of images is 150 pixels that were converted into greyscale before feeding into the model. A separate set of 100 images was used to predict species' label as a form of the classification performance.

The model was optimized by adjusting several hyperparameters such as batch size, number of epochs, kernel size, the filter number, learning rate, and Dropout percentage. For tuning, the Dropout layer with a value range of 0.25 to 0.75 was varied, where 0.25 showed a favorable outcome after the CONV layer and 0.5 after the Dense layer. The architecture was compiled with the *categorical cross-entropy* loss function. After trying out several learning rates such as 0.01, 0.001, and 0.0001 of Adam optimizer, the final rate was selected as 0.0001. With the combination of 32 batch size, the computation was executed for 100 epochs. Each of the results is represented in below plot 40, 41, and 42 with the learning curve and confusion matrix.

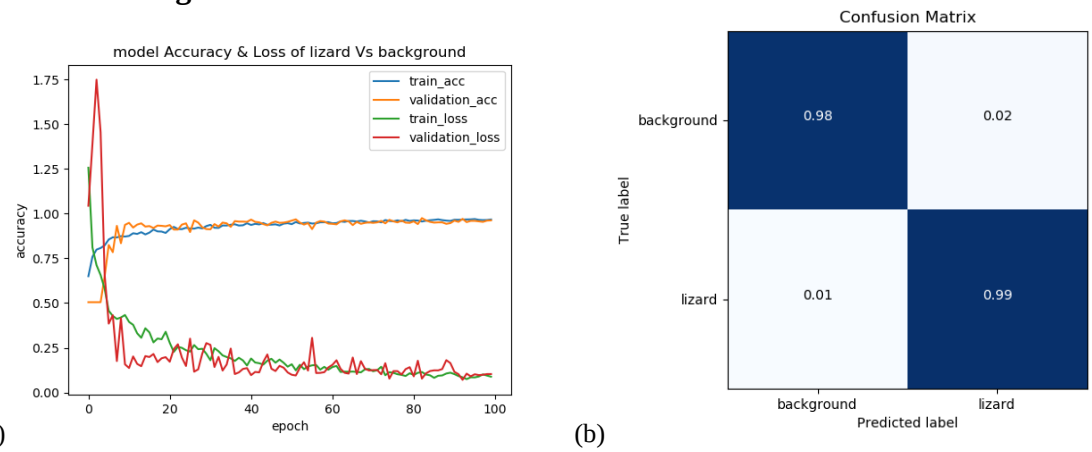
Toad Vs Background



(a) (b)

Figure 40: (a) The accuracy, loss curves (training and validation) with respect to the number of epochs, and (b) confusion matrix of the final CNN-1 model for toad vs background of camera trap images.

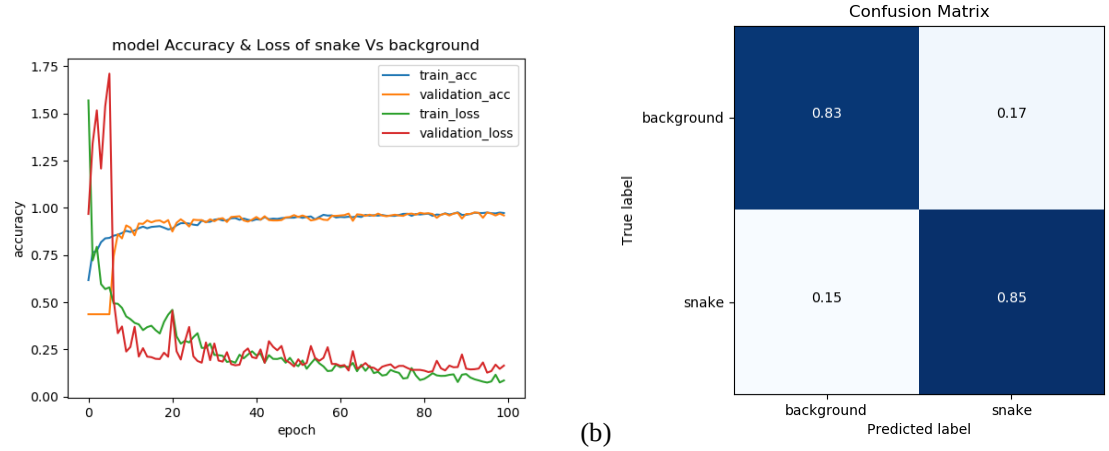
Lizard Vs Background



(a) (b)

Figure 41: (a) The accuracy, loss curves (training and validation) with respect to the number of epochs, and (b) confusion matrix of the final CNN-1 model for lizard vs background of camera trap images.

Snake vs Background



(a) (b)

Figure 42: (a) The accuracy, loss curves (training and validation) with respect to the number of epochs, and (b) confusion matrix of the final CNN-1 model for snake vs background of camera trap images.

Review of the learning curves in Figures 40 (a), 41 (a), and 42 (a) with the confusion matrices in Figures 40 (b), 41 (b), and 42 (b) of CNN-1 can be used to assess the models' performance. All the above learning curves of three different binary problems show a similar trend. The accuracy curves are not showing any sign of overfitting as the validation converges with the training curve. Additionally, the investigation of loss curves shows a continuous declining behavior towards zero value joining the train loss curve. The validation loss curves start decreasing after the 10^{th} epoch and continued until the plot ends. For the toad and lizard dataset, the gap between training and validation is nearly zero, whereas the snake vs. background indicates a slight overfitting tendency after 80 epochs. The result has been summarized in the below Table 8.

Table 8: The overall classification results of CNN-1 models for camera trap dataset.

Camera trap results for CNN-1 (Accuracy in percentage)									
	Toad Vs Background			**lizard vs Background**			**Snake vs Background**		
	Training	Validation	Testing accuracy for toad	Training	Validation	Testing accuracy for lizard	Training	Validation	Testing accuracy for snake
CNN-1 (without Augmentation)	99.86	99.81	99	96.73	96.24	99	97.27	95.96	85

The table 8 and accuracy plot 40 (a), 41 (a), and 42 (a) demonstrate that, within 60 epochs, the models reached around 99% training and 98% validation accuracy for the toad, nearly 96.73% training and 96.24% validation for the lizard, and almost 97% training and 96% validation for the snake images. With a high training and validation accuracy, the toad and lizard scored 99% correctly from the test dataset. Snake recorded 85% test accuracy which is slightly low compared to the other two species in respect of background.

Multiclassification experiment

A multiclassification recognition experiment has been conducted for three of the species together in respect of background images. The results reveal similar pattern as like binary classification as in Figure 43 (a). From the confusion matrix in Figure 43 (b) it has been found that the model was able to detect all the toad and 99% lizard, where 6 background and 5 snake images were misclassified as lizard.

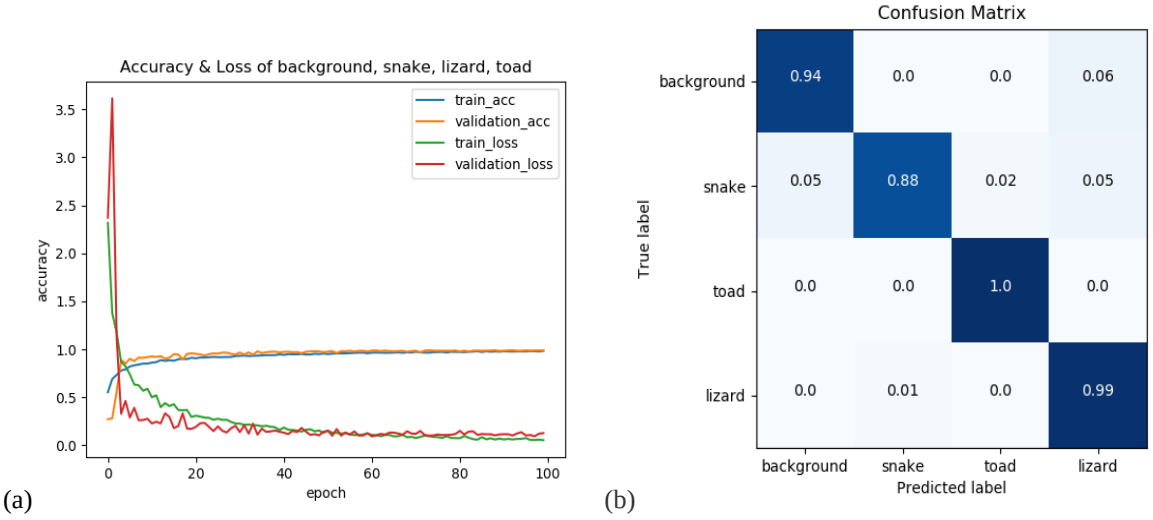


Figure 43: (a) The accuracy, loss curves (training and validation) with respect to the number of epochs, and (b) confusion matrix of the final CNN-1 model for all three species of camera trap images.

Single sample prediction with CNN-1

After training and validating, each model has been saved preserving the configuration, weights values, layers, and parameter information of architecture. With the saved model, a generalization ability test has been done for three the binary and the multiclass model using ten images of each class label. The outcomes are-

- *Toad vs. background:* Nine of the ten toad images are detected correctly; one samples are misclassified as background. All ten background images are classified correctly.

- *Lizard vs. background:* Nine of the ten toad images is detected correctly; One samples are misclassified as background. Six background images are classified correctly, four images misclassified as lizard.
- *Snake vs. background:* ALL snake images is detected correctly. Seven background images are classified correctly, three misclassified as snake.
- *Background vs. snake vs. lizard vs. toad:* All ten toad and lizard images are classified correctly. Eight of the ten snake image is classified correctly. Six background images are classified correctly, four of them misclassified as lizard.

The above test analysis reveals that, all the models were able to generalize an unseen camera trap data according to their training and validation performance. The models show high testing accuracy for lizard, toad, and snake, but misclassified some background as lizard or snake.

8.2.2 Performance Evaluation of CNN-2 (With Augmentation)

The CNN-2 utilizes this augmentation technique in the training phase for the camera trap images by applying different transformation techniques like zooming, shearing, rotating as disccused in chapter 7. The model was tuned with parameters adjustments. After several testing, batch size was kept 32, and learning rate was given the keras default value (0.01). It has been found in experiment session that, the CNN-2 model is suffering through overfitting, so the dropout value has been given 0.5 for all the layers. All the experiments were run for 100 epochs. Each of the results is represented in below plot 44, 45, and 46 with the learning curve and confusion matrix.

Toad vs Background

The accuracy plot in Figure 42 depicts a smooth converge with a training curve with no sign of overfitting. The loss curve is headed downwards, with the training loss having fluctuations. There are several reasons for the oscillation loss curve. First, the training loss is generally computed on the entire training set after each epoch, where the validation loss at each epoch is usually computed on one minibatch of the validation set. This regulation leads to a noisy validation curve as the loss curve considers a small subsample of the validation set, 32 for this model. Secondly, due to the training phase's data augmentation process, the model trained with a modified version of data in each epoch. The validation process did not include augmentation; therefore, the model has a hard time to predict species, which can create fluctuations.

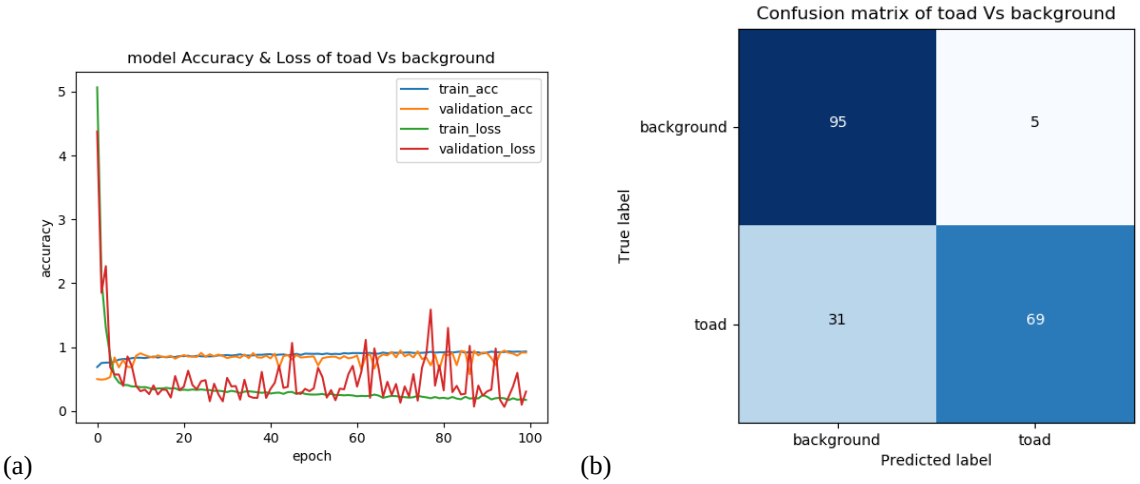
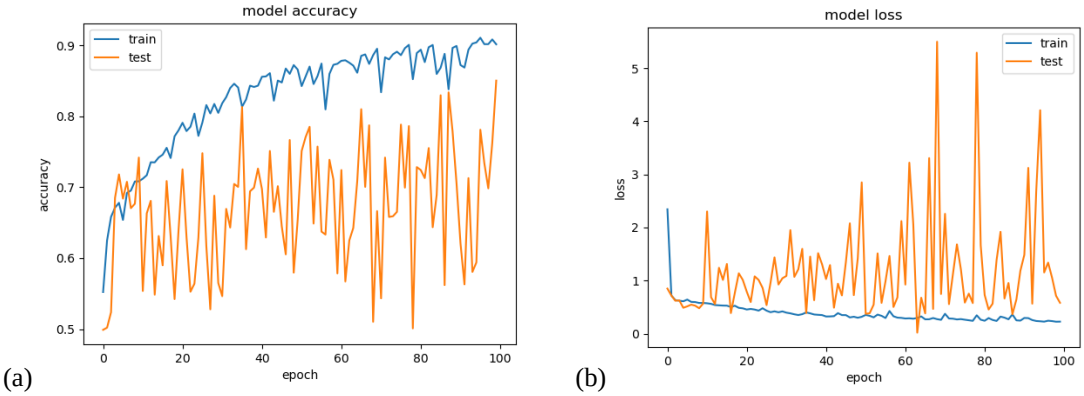


Figure 44: (a) The accuracy, loss curves (training and validation) with respect to the number of epochs, and (b) confusion matrix of the final CNN-2 model for toad vs background of camera trap images.

After 100 epochs of computation, the training accuracy of the CNN-2 model for the toad vs. background is 93.3%, and the validation accuracy is 91.45%. The model recognized 69 toads correctly where more than 30 images are misclassified as background images.

Snake vs Background

The accuracy plot in Figure 45 show overfitting problem having a wide gap between training and validation line. The validation loss curve illustrates noisy movements around the training loss, suggesting that either the validation dataset has too few examples compared to the training dataset or the validation dataset does not provide sufficient information to evaluate the model's generalization ability.



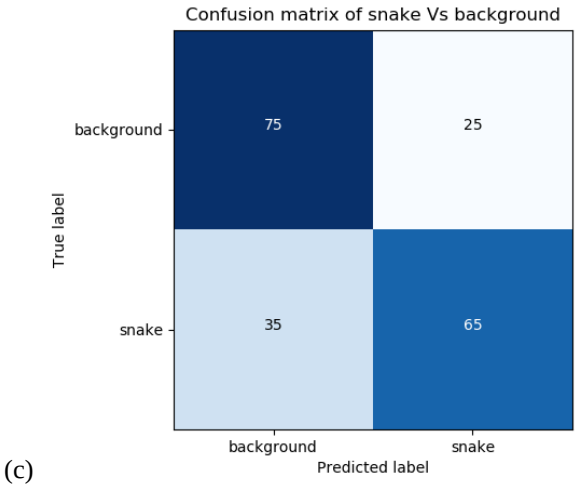


Figure 45: (a) Training and validation accuracy, (b) training and validation loss with respect to the number of epochs, (c) confusion matrix of CNN-2 model for snake vs background of camera trap images.

Even the above confusion matrix shows poor performance on the test dataset where model failed to differentiate a snake image from background. 35% percent of the

snake examples are misrepresented as background in the test data, and 25% of the background was classified as a snake.

Lizard vs Background

Figure 46 depicts the overfitting issue with accuracy and loss curves for the same reason as discussed above. The loss curve is indicating that the validation dataset is unrepresentative as like the training dataset. Also, model is not properly able to generalize the samples of target species.

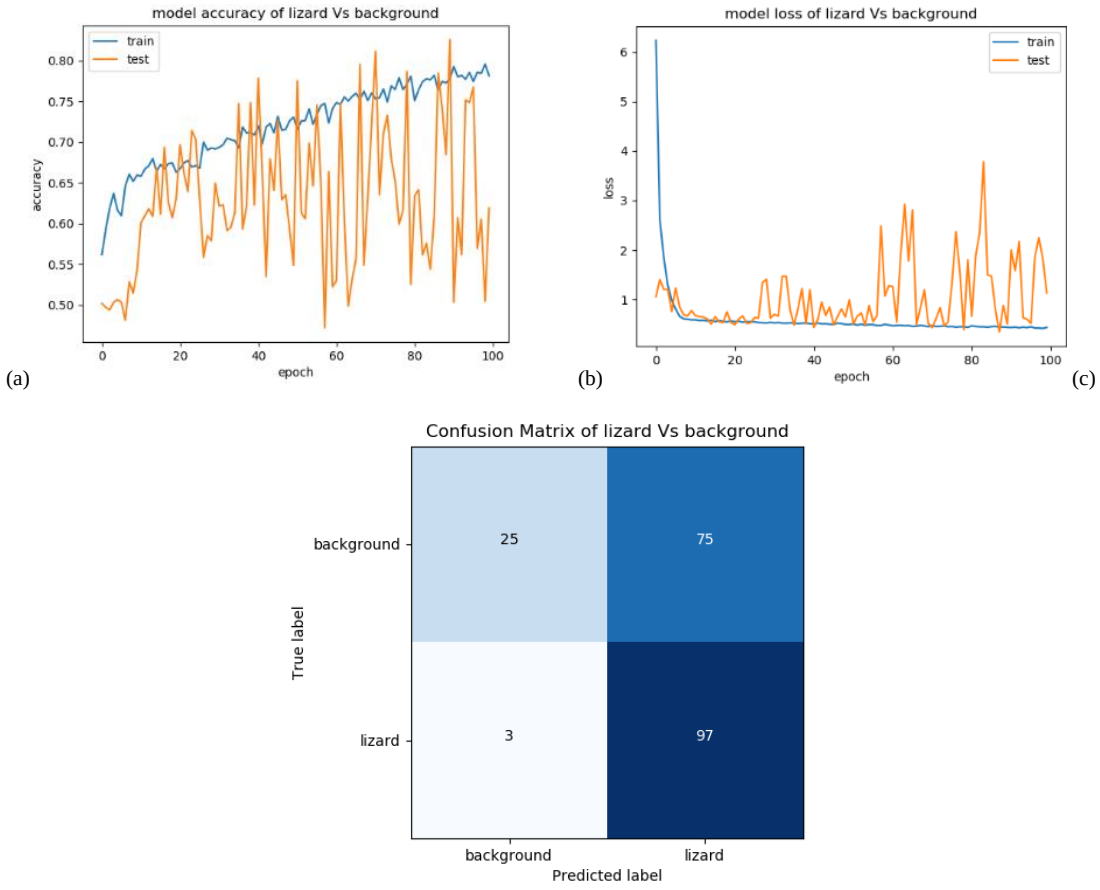
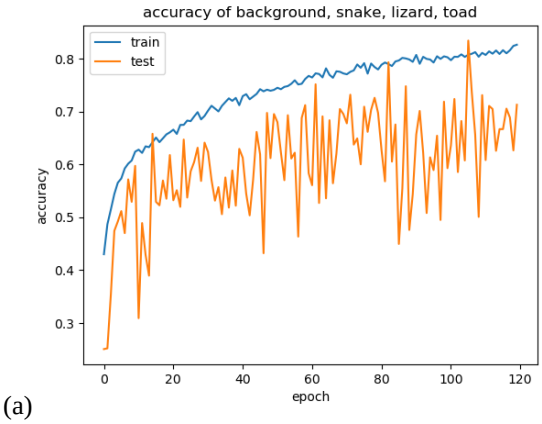


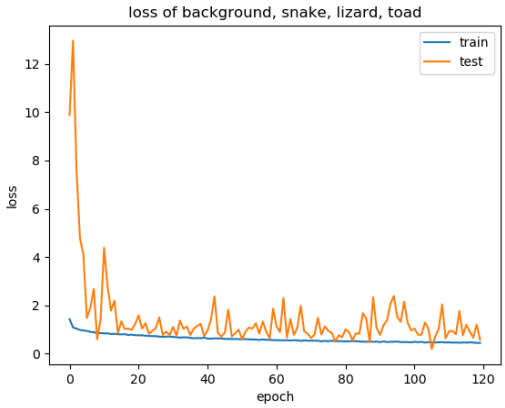
Figure 46: (a) Training and validation accuracy, (b) training and validation loss curves with respect to the number of epochs, (c) confusion matrix of lizard vs background from the CNN-2 model.

Multiclassification experiment

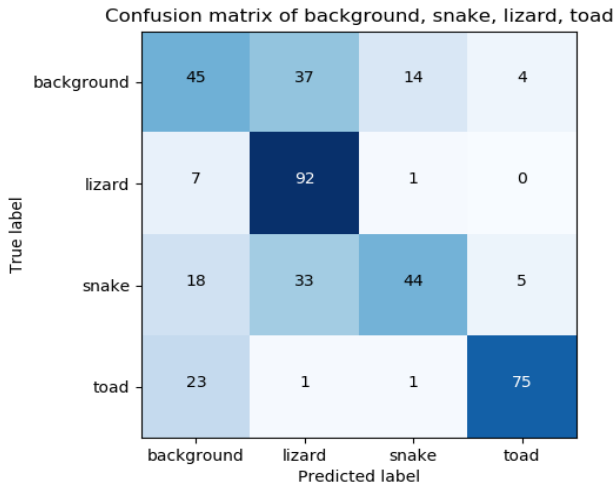
The final DCNN model was trained and tested with all for classes with CNN-2. The obtained learning curve in Figure 47 (a) and (b) and the confusion matrix in Figure (c) yielded similar output as binary classification experiment. The model had difficulty to distinguish each of the species from the test dataset. Among four species, lizard and toad had better performance, though snake was misclassified as lizard and background. As usual background samples were misclassified as lizard.



(a)



(b)



(c)

Figure 47: (a) The accuracy curve, (b) loss curves with respect to the number of epochs, and (b) confusion matrix of the final CNN-2 model for all three species of camera trap images.

8.2.2.1 Attempts to Reduce Overfitting for CNN-2

The above result analysis depicted that the deep learning model performed better on the training dataset than the test set due to the overfitting trend. Many experiments have been carried out to minimize the overfitting phenomenon. The input image size, filter size, number of neurons, learning rate, number of layers and dropout values were systematically varied to understand their impact on classification accuracy. All the CONV and dense layers were incorporated with a 0.5 Drop out value to avoid overfitting. However, this regularization could not prevent the overfitting for CNN-2 models.

Moreover, *EarlyStopping* function has been adopted to mitigate the overfitting issue. After trailing several regularization and hyper tuning process, only *EarlyStopping* shows favorable outcome for lizard vs background and snake vs background experiment as explained below.

Early Stopping

Lizard vs Background

The whole experimental process has repeated for 100 epochs to obtain reliable results with a constant batch size of 32. However, the training process Figure 48 terminated at 60 epochs due to the use of callback function. The learning curve shows a slightly better pattern. But no improvement in the validation accuracy has been observed Surprisingly, the testing accuracy as in Figure 48 (c) has increased moderately from the previous execution. The advantage of using callback function is to reach the same accuracy within a smaller number of epochs, and computation time. The testing accuracy has increased moderately from the previous execution.

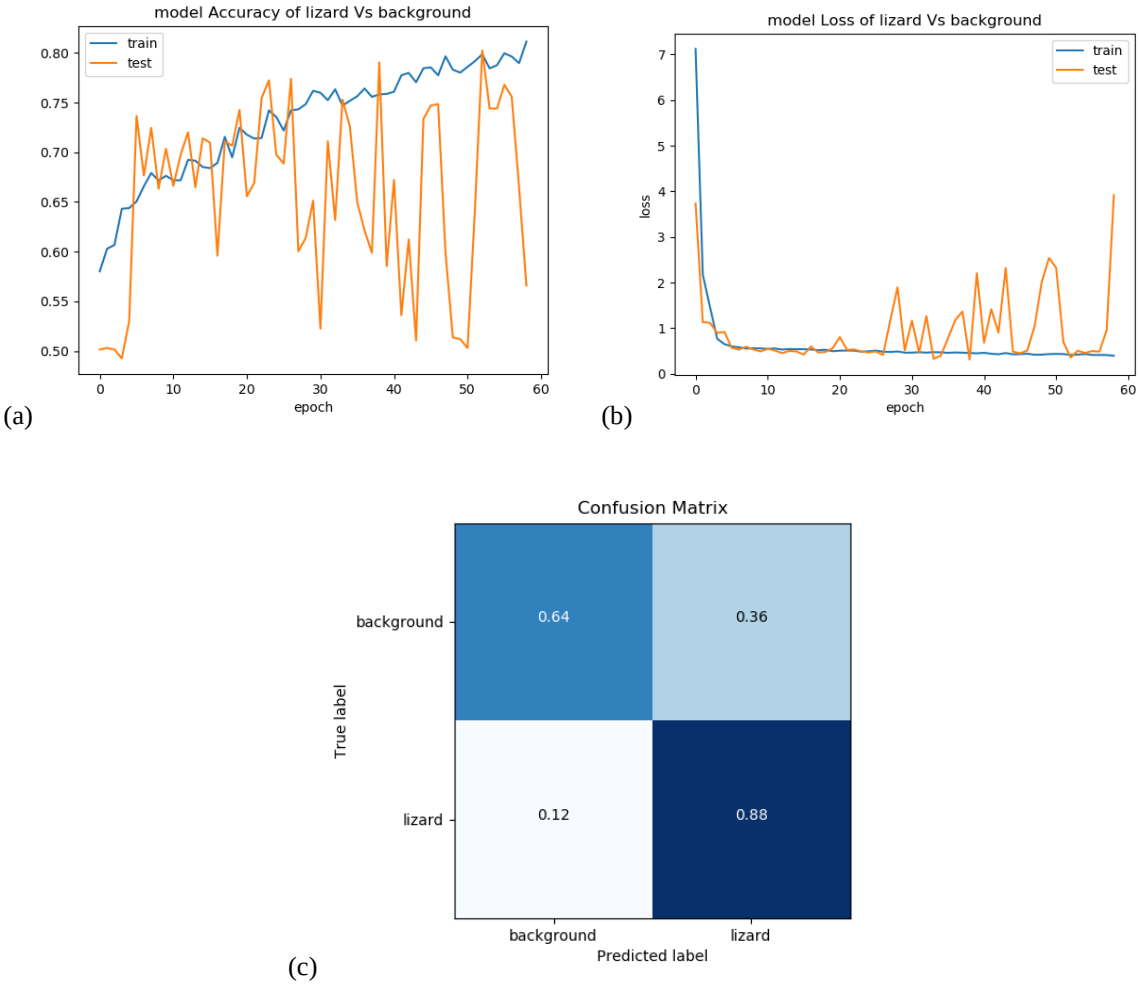


Figure 48: (a) Training and validation accuracy, (b) training and validation loss curves, (c) confusion matrix of lizard vs background after using early stopping function of CNN-2 model.

Single sample prediction with CNN-2

The findings from the generalization ability test of the CNN-2 using ten images of each class label-

- *Toad vs. background:* Nine of the ten toad samples are misclassified as background. All ten background images are classified correctly.
- *Lizard vs. background:* All of lizard samples are misclassified as background. All ten background images are classified correctly.

- *Snake vs. background:* Seven of the ten snake images is detected correctly; three samples are misclassified as background. Six of the background images are misclassified as snake.
- *Background vs. snake vs. lizard vs. toad:* Two toad and five snake images have recognized correctly.

In can be noticed that, data augmentation shows promises only for snake images, where this method failed to improve recognition accuracy for lizard and toad. CNN-2 architecture predicted all the ten lizard samples, and 90% toad samples as background. As expected, the model performed well for snake identification providing 70% positive accuracy. However, this model also misclassified 60% background image as snake.

8.3 Discussion and Findings

1) Two deep learning frameworks, CNN-1 and CNN-2 were developed to recognize animals from image data automatically. First, the models were trained and validated with online dataset to solve a binary (toad vs snake) recognition problem, and later, the work was extended to classify three species together (toad, snake, and lizard). The results demonstrate satisfactory level of performance for online sample set for both models as represented below Figure 49-

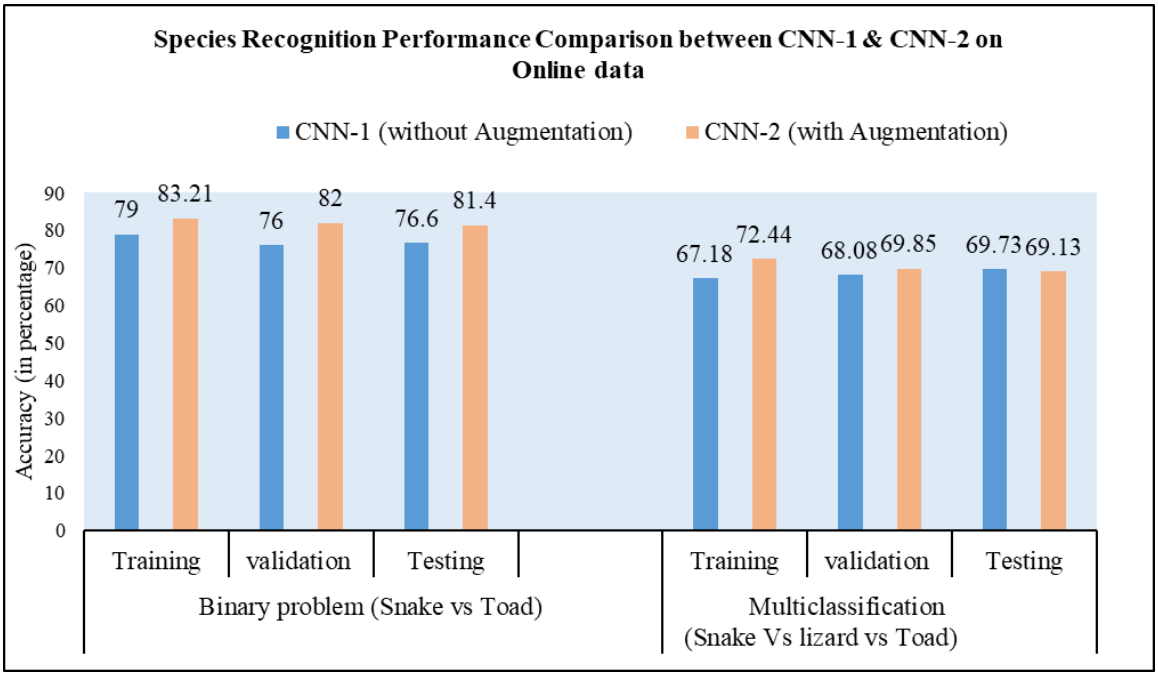


Figure 49: The overall classification result of CNN-1 and CNN-2 models for online dataset for both binary and multiclass problem.

The above figure shows that, applying various image augmentation regimes in CNN-2 helped to improve a moderate amount of training and validation accuracy compare to CNN-1 for classifying two species, or three species together. Another finding from the assessment of the binary and multiclass is that, increasing class size lowers the performance of the models as additional samples and intricate features increase the classification complexity within their group.

2) Afterword, the models are trained with camera trap data to recognize target species. CNN-1 provided remarkable training, validation, and testing accuracy for given samples with no overfitting issue. This model was able to recognize 99% toad and lizard, and 85% snake image from a test dataset of 100 examples as in below Figure 49. There are certain reasons behind the optimal results of the binary classification problem of camera trap images and they are-

• In CNN-1, all the samples are being trained for 100 times in the algorithm. In each epoch, the model is learning information from the same images, leading to a high training and validation accuracy.

• Most of the toad and lizard samples had the similar background sequence, as explained in the dataset chapter. Due to the less variation in the image, the model learned the samples very well, showing high evaluation accuracy.

• The original 600 toad samples have been increased by rotating 180 degrees, and added in the existing dataset, which produced repeated versions of the same image. Also, most of the toad images are night vision samples providing the benefit of a less cluttered background compared to other species images. Due to less complexity and disparity, the learning curve and test accuracy of toad show optimum results as seen in below Figure 49.

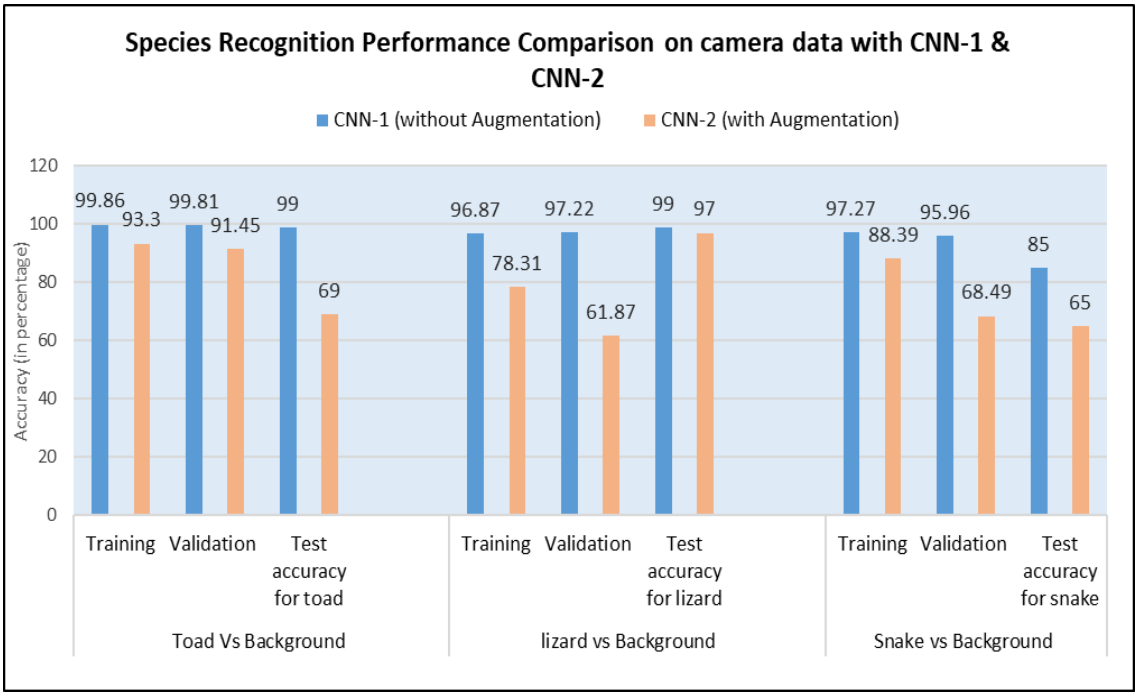


Figure 50: The overall binary classification result of CNN-1 and CNN-2 models for camera trap dataset.

Conversely, a poor performance has been observed for CNN-2 models for all the species. The accuracy curve of the binary algorithm of CNN-2 illustrates overfitting issue in the accuracy curve. The accuracy plots in Figure 43, 44 and 45 reveal that, the dataset does not provide sufficient information to learn necessary features or useful patterns of target species by the architecture. Therefore, the model is unable to prove the ability to generalize images from validation dataset. As a result, the performance was degraded compared to CNN-1 model.

3) Various research suggests that, data augmentation helps to improve generalization ability of images and boost the robustness of a CNN model. This has been proven in phase one, where the accuracy has been enhanced after applying augmentation technique for online data. Hence, for the camera trap images, it did not improve due to the following reasons -

(a) The CNN-2 models suffer from data deficiency. Moreover, in the dataset, the samples have adjusted artificially to increase the dataset, eventually failed to obtain the target class's feature.

(b) Due to the augmentation procedure, the model is training with a new set of slightly modified data in each epoch. As the model sees a new set of transformed images which is replacing the previous set, it is unable to learn the individual meaningful pattern of species.

(c) Toad and lizard are too small to recognize with respect to the background information. Moreover, the lizard and toad body shape, size, color have very high similarity background properties.

(d) The snake images have advantages over other species with a considerable amount of body size, shape, and diversity, which allow the algorithm to learn about the distinct features and make them separate from a background image.

Also, it can be noted that, the generalization test has been done with 10 sample per species. Conducting test process with more images might increase the prediction accuracy for target species.

In conclusion, CNN-1 shows higher efficiency to predict camera trap data into their label between the two models. Moreover, the advantage of CNN-1 is that it requires less computation time and memory to train the dataset, while CNN-2 takes longer time to compute as it generates a new set of augmented samples of the existing data in every epoch for training purpose.

4) After several experiments it can be summarized that, a significant number of

imagery data, and a robust network can minimize the misclassification error providing a good recognition accuracy. Also, an alternative labeling method such as ground truth labeling can be investigated to teach the models about the complex features of species of a challenging sample set.

5) To explore the potentiality of region based convolutional neural networks (RCNN), a test has been conducted with the pre-trained ImageNet model: residual neural network (ResNet). In this region-based object detection technique, the model tries to identify the location of a target object of interest in an image, and then classify them to obtain final object detections [76]. A pixel-based clustering algorithm is applied that attempts to merge the similarities of color, texture, size, shape of object [76]. Afterward, the model seeks a final meta-similarity to find a region of interest and then provides the predicted score [76].

Some of the observations from the pre-trained ResNet model is included in Appendix B. The pictures clearly reveal that, the ResNet neglected the target species in the camera trap images and selected wrong objects location. Also, the model provided incorrect prediction of the bounding box coordinates of the marked object location. The reason is that ResNet is not trained with this particular data samples. The model needs to train with camera trap dataset with appropriate labeling and annotaion of target species. With proper training, the RCNN algorithm can be investigated in future for far more accurate classification and object localization experiment.

9. CONCLUSION AND FUTURE WORK

The challenges associated with big data need to overcome with a structure that will systematically and efficiently analyze information. A justified initial work of species classification for phase one is presented with online images that depict potential success for camera trap images. The experiment result demonstrates the feasibility of recognition of animal species. Necessary changes have been made while training the original camera trap images to reduce the effect of data imbalance and varying object position, lighting, and weather condition challenges. However, real-world samples exhibit natural adversarial prone, lowering the performance to recognize species from images. For CNN-1, the average testing accuracy for toad and lizard is 99% and for snake is 85% with respect to background examples. Nevertheless, in the generalization ability test from a separate set of unlabeled data, this model recognizes 90% toad and lizard, and 100% snake species from a set of ten images for each species. This results suggest that, for the same background environment, CNN-1 model will be able to recognize species.

An alternative CNN architecture has been experimented to explore various augmentation effects in the model by enhancing the amount of dataset and exploiting specific properties. This process allows to train the model with a wide range of object variations in form and shape. The binary classification experiment test accuracy of CNN-2 for toad, snake and lizard is 69%, 65% and 25% consecutively with respect to the background. In the generalization ability test, the training techniques with augmented samples have a practical effect on a snake, adding no toad and lizard progress. In other word, CNN-2 failed to distinguish lizards and toads from the background.

The results of CNN-2 validate that, the CNN framework will be able to recognize the target species if the quality, and background view of the image belong to the similar circumstance that have been provided for this project. Any changes in the target species such as body size, shape, or the nature of presence of species in the surroundings, may decline the recognition percentage. Both the models, (CNN-1) and (CNN-2) will perform better in the classification process when objects or species have a decent presence in a sample or have a pixelated value in the background.

Nevertheless, the above issues always will be a part of the problem in automatic identification process with camera trap images. For snake identification, a sufficient amount of data will enhance classification accuracy. The current models have substantial room for improvement by making it more robust to detect challenging animal species from the camera trap dataset. In order to determine the optimal recognition method, further research is needed. Several deep learning architectures can be explored to find a better recognition solution for three species, such as Region-based Convolutional Neural Networks (RCNN), U-Net, and other deep learning networks.

APPENDIX SECTION

Appendix A

In an attempt to minimize overfitting and increase generalization ability in CNN-2, several regularization techniques have been experimented in the architecture as explained in section 8.2.2.1. The CNN-2 model was tested with a variety of combinations of small learning rate and higher batch size that did not perform well in the validation and test data. Also, a two-layer shallow model has been designed to ensure less complexity in the model. Hence, the result was not improved. That is why the below two result has been added in Appendix A.

Small Learning Rate and Higher Batch Size

An experiment was performed with a learning rate of 0.0001 and a batch size of 64 to minimize the overfitting effect in CNN-2. Still, the overfitting trend was not improved from the previous one, as seen in Figure 51. The model predicted worst for the testing sample set having background misclassification.

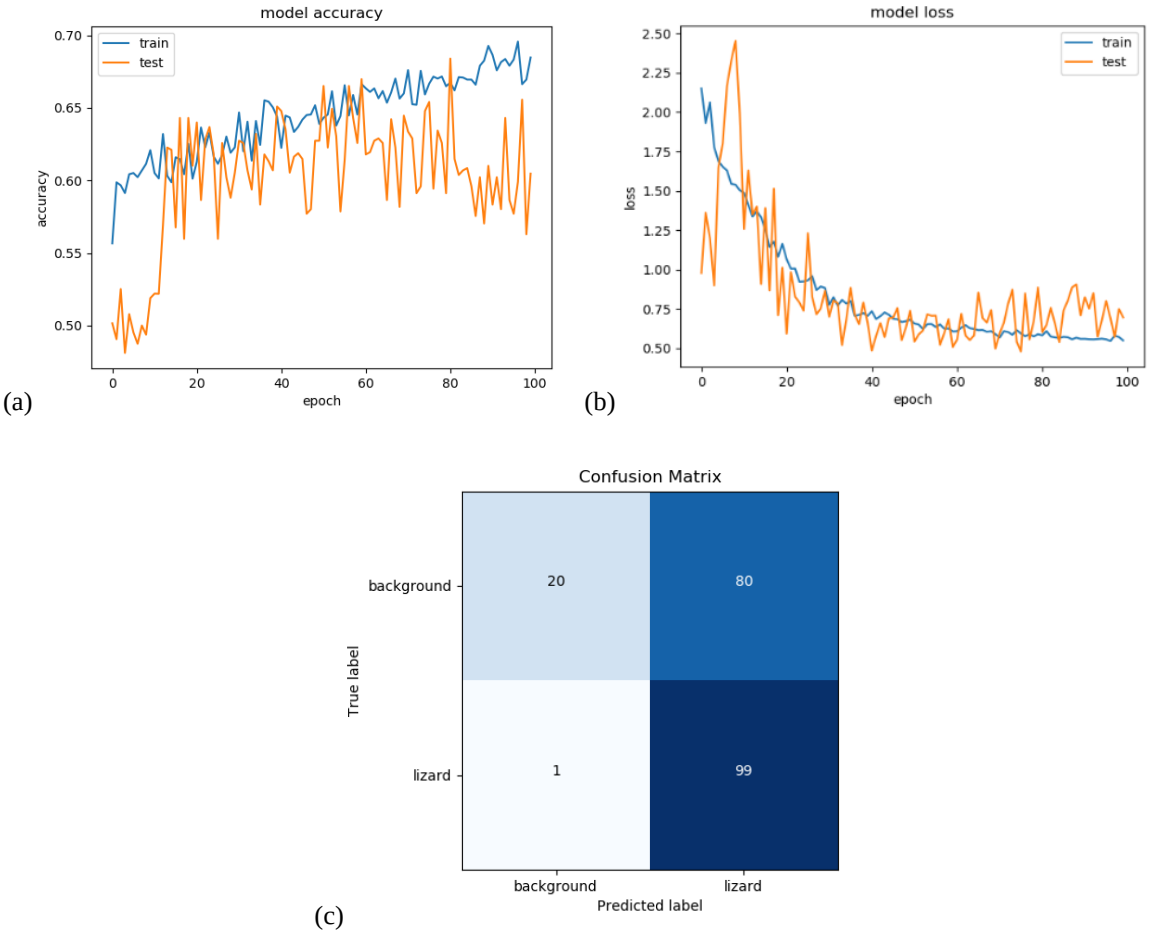
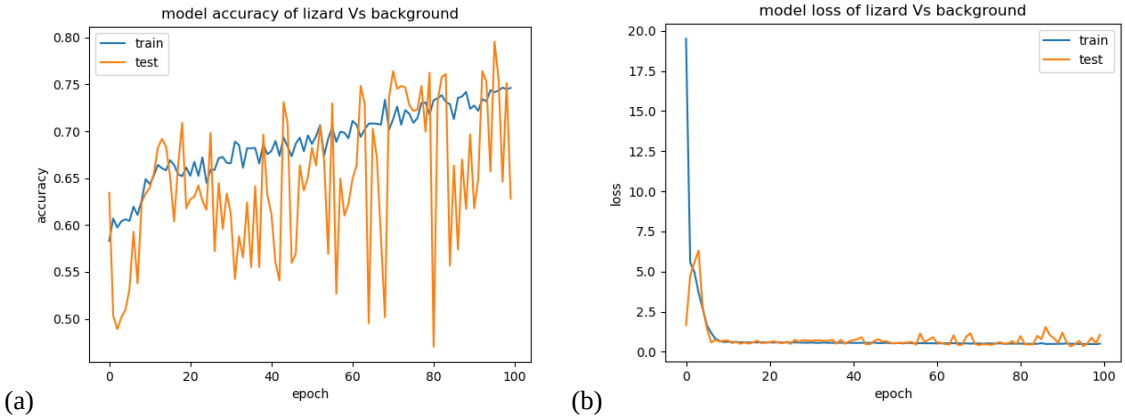


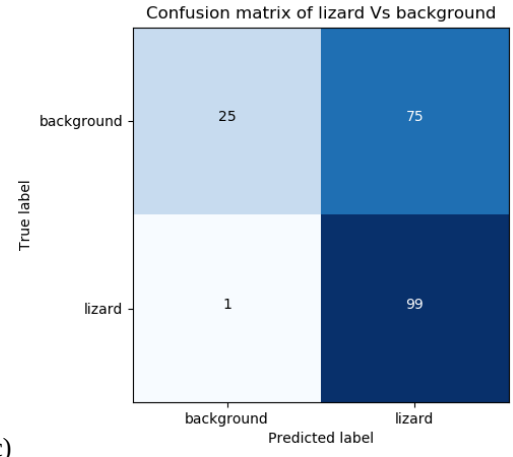
Figure 51: (a) Training and validation accuracy, and (b) loss curves with respect to the number of epochs and confusion matrix of lizard, and background for CNN-2 using small learning rate and higher batch size.

A Shallow Model with Two Convolutional Layer Set

A two-layer architecture has been constructed with two Convolutional layers with 32 filter size and 64 filter size in the dense layer. The attained training accuracy is 74.63%, but the validation accuracy dropped at 62.81% indicating no improvement in the performance. Also, the model was not unable to distinguish between background and lizard in the test dataset.



(a) (b)



(c)

Figure 52: (a)Training and validation accuracy, (b) loss curves with respect to the number of epochs, and (c) confusion matrix of lizard, and background for CNN-2 using a shallow model with two convolutional layer set.

Appendix B

Testing Camera Trap Images with a Pre-Trained ResNet Model

The below Figures are the test result of RCNN object detection algorithm where the pre-trained ResNet model failed to predict the target object location (or species region) and classify with proper annotation for camera trap samples. Below figures show the inaccurate prediction results for lizard, snake, and toad images in Figure 53 (a), (b), and (c) consecutively. In Figure (a), the RCNN model ignored a lizard and created bounding box around a wired mesh drift fence and labeled as “lacewing”. The model misrepresented a part of snake as “centipede” in Figure (b) and misclassified a toad sample as “armadillo”. The prediction accuracy can be further improved by retraining the model with proper object labeling and appropriate annotaion.

(a) 

(b)

(c)

Figure 53: R-CNN test result of (a) Lizard sample, (b) snake image, (c) toad example with bounding box and prediction.

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