RESEARCH OF WATER DETECTION IN AUTONOMOUS VEHICLES

by

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DEDICATION

To my family and friends,

for their endless support and love.

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LIST OF ABBREVIATIONS

Abbreviation	Description
UGV	Unmanned Ground Vehicle
LiDAR	Light Detection and Ranging
RADAR	Radio Detection and Ranging
GNSS	Global Navigation Satellite System
PBS	Polarizing Beam Splitter
MSS	Multi Spectral Scanner
IR	Infra-Red
RF	Radio Frequency
BSP	Binary Space Partition
FPGA	Field Programmable Gate Array
BOV	Bag-of-Visual
NN	Neural Network
ANN	Artificial neural Network
CNN	Convolutional Neural Network
GAN	Generative Adversarial Network
RGB	Red Green Blue
NIR	Near Infra-Red
HSI	Hyper Spectral Image
IMU	Inertial Measurement Unit
GNSS	Global Navigation Satellite System
V2V	Vehicle-to-Vehicle
V2I	Vehicle-to-Infrastructure
I2V	Infrastructure-to-Vehicle
I2I	Infrastructure-to-Infrastructure
DSRC	Dedicated Short Range Communication

Abbreviation	**Description**
WAVE	Wireless Access in Vehicular Environments
LTE	Long Term Evolution
SLAM	Simultaneous Localization and Mapping
DATMO	Detection and Tracking of Moving Objects
SURF	Speeded-Up Robust Features
GPU	Graphics Processing Unit

ABSTRACT

An autonomous car is a ground vehicle that navigates without human input. These vehicles are expected to reach $60 billion in sales by 2025. But these autonomous vehicles have many drawbacks: one among them is lack of water detection. This problem has created havoc in the normal operation of autonomous vehicles which has interested researchers to develop algorithms to overcome this problem. This research aims to address the fundamental challenges pertaining to this issue using image classification. For this task we first design a general image classification system for water detection and propose a heuristic solution to classify the images. Secondly, we adopt a machine learning technique and develop an algorithm to classify the images. We consider the same image data set for both the models. The results show that the detection of water in three different climatic conditions is feasible and convenient for the proposed model. The results from the proposed image classification system for gray scale and color and the machine learning technique are different, and the image classification model has more accuracy than the machine learning technique.

1. INTRODUCTION AND LITERATURE REVIEW

1.1. Research Motivation

For the past ten decades, transformations within the automotive category have created cleaner, easier, and more affordable vehicles. The industry now appears close to significant change, caused by self-driving or autonomous vehicle technologies. An autonomous car is a ground vehicle that navigates without human input. To achieve autonomous vehicle activity in urban areas with unpredictable traffic, many real-time systems need to communicate, including environmental recognition, localization, planning and control [1]. Self-driving vehicles offer the promise of noteworthy benefits to society, increasing mobility, decreasing crashes, and they combine sensors and software to control [2].

An integrated automatic driving system consists of planning, perception, and control. Road and highway infrastructure surrounding the driving vehicle will also play a great role. The technology present in the vehicle will retrieve and send information from the road through laser sensors and cameras, logging information on road conditions as quickly as 10 times per second through transmitters. Thus, in time, we will see our roads and our cars streaming information back and forth, from road to vehicles and from vehicles to road [3].

The problems in autonomous cars can be divided into several tasks [4]. These tasks can be categorized like the movement of the vehicle should be in a specified path and when the appropriate decisions should be taken by the vehicle when any unpredictable situation arrives like pedestrians walking on the road, children playing on the streets, when there is water present on the road during rain, traffic signalization, etc.

One of the main problems is when the autonomous vehicles cannot detect the water that is present on the surface of the road. The vehicle may lose control, damage property, or cause serious accidents if it maintains the same speed as when there is no water present on the road. Due to these problems it is not a good idea to use autonomous vehicles on the road in which the detection of water is not achievable when there is water present.

In the proposed solution, it can be observed that the detection of water which is present on the surface of the road is possible. In general, a complicated hardware system with software is involved in the car for object detection. Object detection and object classification mechanism in an autonomous car play a crucial role in operation of the vehicle to act accordingly depending upon the situation. The proposed algorithm is designed with concept of image processing and uses various other properties of an image in classification process. The image classification algorithm and machine learning algorithm are designed as a software model.

1.2 Literature Review

1.2.1 Sensor Technologies

Detecting water is a significant challenge to unmanned ground vehicle (UGV) autonomous off-road navigation [5]. A car traversing a wet road must adapt the driving style accordingly, reducing the speed and increasing alertness [6]. Water detection can be done by using various sensor technologies which are in existence, and by using the concept of image processing. The various sensor technologies that can be used are Light Detection and Ranging (LiDAR), Radio Detection and Ranging (RADAR), Ultrasonic sensors, etc.

Radar and multi-spectral sensors are used for mapping surface water systems. Conventional land-based techniques should be complemented by using satellite and airborne remote sensors to survey large areas of water. Satellite gravitational surveys and satellite remote sensors can be used with additional data analysis to water behavior from surface expressions. The above-mentioned methods usage is appropriate for large water bodies. Water on roads while raining, stagnated water, lakes, rivers, etc., come under the category of surface water [7].

24-GHz automotive Radar technology is used for detecting low-friction spots on asphalt caused by water, snow, or ice. The surface scattering model is used to study the back-scattering properties of asphalt. The different conditions of these properties in asphalt are studied in both field and laboratory experiments. By comparing the radar with the back-scattering signal at different polarizations, the low-friction spots can be detected. The back-scattering properties of asphalt are more affected by water. So, the water can be detected it is in larger portions. Dual purpose antenna with a switch at both the ends, that is at transmitter and at receiver end could be used for a commercial automotive radar. A switchable antenna is required for a multi-purpose radar such that the beam can be switched between the direction of motion of vehicle and the road surface [8].

Global Navigation Satellite System (GNSS) is one of the best precise localization systems. In an urban environment, since there is lot of noise and the signal is disturbed by the surrounding buildings and other structures, GNSS always cannot reach the level of precision in centimeters range. The high-quality sensors are costly, and the stereo vision requires powerful hardware to process the cameras information. The data fusion algorithm and low-cost architecture of sensors are capable of autonomous driving in narrow two-way roads. This approach is a combination of a dead reckoning system and a short- range visual lane marking detector guides the vehicle to move in a desired path but does not help in different climatic conditions [4].

In LiDAR technology there are different types like topographic, bathymetric, and terrestrial. Of these, Bathymetric lidar technology is mainly used for water detection. This technology uses green light or infrared light or both. Bathymetry on continental hydrographic networks is up to now limited to small areas. To expand river bathymetry surveys, bathymetric, LiDAR is an interesting tool. Very few studies focus on water depth measurement accuracy, in particular for rivers and for very shallow water.

Mapping shallow-water bathymetry with acoustic techniques is very difficult and expensive. It is more variable, and it also greatly impacts the depth extraction from the survey measurements as the environmental parameters are less than 2m in shallow-water areas. Current airborne LiDAR bathymetry surveying in shallow-water depths uses green-channel waveforms to measure the water depth. Unfortunately, due to difficulties in distinguishing between the surface and bottom return of the water column, the timing of the bottom return is often ambiguous. Furthermore, the water often becomes optically “dirty” due to turbulence at these shallow depths. The red-channel wave forms are used instead for green light [9].

Using a single photomultiplier tube is employed for applications of shallow water depth measurement which transmits at 532 nanometers. The polarizing beam splitter (PBS) is used as a medium to transmit the vertical linear polarized light and it receives signals between depolarized water returns and polarized water returns. By employing the polarization states the bathymetry bandwidth limits are adjusted. The water depth considered is one centimeter (1 cm) with ±3-millimeter uncertainty. For better depth determination different wavelengths can be considered while on the other hand improving the detection of signal [10].

Autonomous car was fed with unsupervised algorithms that automatically calibrates a 64-beam rotating LiDAR with high accuracy. For localization with centimeter accuracy, the high-resolution maps of the environment are generated. The updated version of the recognition and perception algorithms allow the car to classify obstacle as vehicles, pedestrians and cyclists and also traffic lights. The improved controller brakes, accelerates, etc., according to the situations. These algorithms work under different climatic conditions. It is necessary for a driver to be present all the times, since this car cannot be driven for hours and may be not be switched occasionally when unexpected events occur [1].

The accident rates of all the vehicles are increasing by 25% a year on an average [11]. It is possible to remotely detect the presence of water on the surface, by using infrared (IR) detectors sensitive in the water absorption spectral range. Using the IR sensor technology, it is easy to identify the presence, but the form of water present on the surface should be identified first: snowy, ice, etc. the sensor that contains three IR detectors the highest sensitivity in describing the condition [6].

All the LiDAR and Radar sensor technologies work on the same principle: a signal is sent and the time that a signal takes to come back is measured. Optical methods are very accurate. RADAR uses high frequency RF (radio frequency) signals.

The Ultrasonic sensors technology is similar to radar but instead of RF signals, ultrasonic waves are sent. In ultrasonic sensor technology, the distance is measured until the presence of a target object or material through air.

In radar based remote sensing the major challenge is to identify and detect the targets. Especially this applies to spatially distributed, multiple targets. Earlier the concept of multi-spectral analysis were used for the water level measurement. Now, this approach is used for scanning RADAR applications. The variance of the signals is used to differentiate the levels. Large noise signals are supressed which are present in different scenarios for various disributed targets. The evaluation of the concept is performed by scanning 75 to 80 GHz Frequency Modulated Continuous Wave(FMCW) radar system. This concept also helps in distinguishing the radar targets [12].

1.2.2 Other Technologies

A stereo pair of color lenses are used for the detection and localization of the water bodies during daytime. The presence of water can be observed from the texture, color, and the detection of terrain reflections in stereo data. These are generally used for large water bodies. The elevation of water bodies can be detected by using the ground detection algorithm. And it also helps in giving the accurate location. The false detection in the world map is suppressed and the detected water body elevation is improved by the temporal filtering [13].

The autonomous car system can also be enhanced by using infrared thermal imaging. To distinguish false water pixels instead of a mirage detected from stereo imaging, the thermal imaging can resolve this problem. Water flow rate on the road is a function of road tilt and banking apart from factors such as current weather. Using a tilt sensor and images can give an estimate about the water flow and can be used control the speed of an automotive.

Image processing technology can be used for a real time water monitoring system. The two real time systems for monitoring are the water level recognition and the surface velocity recognition. For water level recognition, image processing techniques like binarization, water line detection and object recognition are used. For the surface velocity recognition, particle image velocimetry by the cross-correlation analysis may be employed. The above proposed systems are used to measure and record the variation in the surface velocity and water level. The two mentioned methods are tested in different climatic conditions [14].

The representation of an image's content is still a challenging issue in the field of image processing. To preserve the scene semantics of image contents, BSP tree structure representation is useful. The images in this process are partitioned into sub images by straight lines. Then line quantization process and line selection process is applied to select the lines that are partitioned from the set of quantized line based on an entropy approach. This approach was tested on the classification of different scenery images. Good results were achieved from the performed tests on the natural scenery images [15].

Successful road navigation by UGV requires reliable preception of terrain. The precipitation algorithms generally detect driving hazards. The precipitation sensors are mounted on a UGV. The two ways to detect the driving hazards is by primary obstacle detection and traversability cost analysis. For cluttered environments, some method of a cost analysis of traversability is necessary. Jet Propulsion Laboratory has investigated both methods using stereo vision systems. To perform stereo ranging during the daytime, color cameras are used. And to perform stereo ranging during the day and nighttime, thermal infrared cameras are used. A set of binary detectors has been implemented that detect definite obstacles, contrary obstacles, water bodies, etc. UGV autonomous navigation independently with active and passive sensors. As advances in computing hardware improve, the stereo range data enable advanced stereo algorithms that are to be performed in real-time, further closing the quality gap between stereo and lidar [16].

The hyperspectral image classification can be achieved by the spatially constrained Bag-of-Visual Words (BOV) [17]. From an image, two types of low-level features are extracted: texture features and spatial features. The high-level visual words are constructed by using the features from the low-level extracted features. The homogeneity of the regions is retained by using the super pixel segmentation methods entropy rate, which further helps in segmentation of the hyperspectral features into patches. With this, the BOV has all the statistics from different patches in the form of words. This experiment is performed on the real data and is also compared with the several state of the art methods [17].

The RADAR system can detect and classify the objects or targets by applying Levenberg-Marquardt algorithm on an Artificial Neural Network (ANN). The different sets: training and test set in ANN contain high-resolution Inverse Synthetic Aperture Raday pictures that are collected by the detection module of radar. From the simulation results obtained, it can be observed that the system is able to detect and differentiate the objects and also the radar system can surpass the human operators. These results indicate that the human radar operators can be potentially replaced by the future intelligent systems[18].

The prior works which were carried out for object detection depend on the instances of an object. And many number of algorithms are used in every step of detection process which thus reduces the efficiency of overall circuit or the network. The object detection task can be performed as a regression problem. The deep hierarchical features from a Convolutional Neural Network (CNN) are employed to improve small size object detection. This hierarchical architecture combines the semantic information appeared from a deep layer with the appearance information from a shallow layer. This approach can predict the probabilities of a class and bounding boxes from the input image [20].

Data augmentation is a process where the diversity of data is increased. This data is generally used for training models. For training the network large amount of new collection of data is not required. The data augmentation can be done simply by cropping an image, rotating an image and also by flipping the input images. There are many other simple techniques for data augmentation. Sometimes the data set is constrained to a small subset of ImageNet dataset and compare data augmentation technique in turn. The Generative Adversarial Networks (GAN's) are also used to generate different style of images. A method is proposed to allow a neural network to learn the arguments so that the classifier performance is improved. But the GAN's and neural augmentations consume most of the computer time almost three times. So always combining the traditional augmentation method followed by neural augmentation is advised [21].

The deep NN's has led to the development of a state-of-art- object detector which is termed as Faster Region based CNN (Faster R-CNN). To detect an object in this model the information is extracted from two modalities: near-infrared (NIR) and color (RGB).

These fusion methods were earlier explored because of the combination of multi model information that is with RGB and NIR. This past model led to a faster multi model R-CNN in which the results are accurate and compilation time is faster. The precision and the performance increased from 0.807 to 0.838 for the detection of a black pepper. This approach is quicker since it requires a boxing annotation than a pixel-level annotation [22].

The core task of the remote sensing community is Hyper Spectral Image (HSI) classification. A lot of images are required for training the network. The deep learning method can be used for the classification of HSI's and its proven. Sometimes the manually designed architecture may not fit a specific data set very well. Various operations like pooling, convolution, batch normalization and identity are selected. Then an algorithm is selected that effectively find the deep architecture which is the evaluated on the validation set. Next, the best CNN model is selected for HSI classification. The automatic 3-D Auto-CNN and 1-D Auto-CNN are used as spectral-spatial HIS classifier and spectral classifier respectively. This experiment is performed on four data sets. And the results collected were accurate when compared with the state-of-the-art methods, so in future id there is a large image collection of dataset this method might be applied. [23].

1.3 Thesis Outline

This thesis is composed of the following chapters: Chapter 1 is an introduction to car sensors along with a review of previously developed sensor technologies. Following this, chapter 2 focuses on the developmental timeline of autonomous cars. Chapter 3 discusses the procedural steps for image capturing and measurement setup. Chapter 4 describes the algorithm used to analyze the datasets. This chapter explains the results of image classification. Chapter 5 discusses the machine learning algorithm and its results. Chapter 6 concludes the research and includes suggestions for future work.

2. AUTONOMOUS CARS

2.1. Introduction

Autonomous cars are also known as self-driving cars or driverless cars. Self-driving car means the operation of a car without any human input. The autonomous driving has progressed from “maybe possible” to “ possible” to “undeniably possible” to “inevitable” and now to “commercially available”. The millennials and generation Z are motivated by the survival instinct and by the interwoven forces of opportunities. The driverless car technology might add $7 trillion to the global economy [24].

At present, many semi-autonomous vehicles are observed on roads which are fully autonomous due to few safety constraints. Self-braking and assisted parking systems come under semi-autonomous driving. But few vehicles have a capability to brake, park, steer and drive themselves. The technology that has not yet been perfected for a vehicle to be fully autonomous. Some predictions show that the vehicles might be fully autonomous and can drive completely without any human input by 2025 [25].

2.1.1 History

The concept of a self-driving car came into the light in the year of 1939 in New York’s Fair. There was an exhibition that was created by General Motors to show the vision of what world would look in 20 years from then and it had self -driving cars that would be used on automated highways. The technologies then were all focused on the concepts of robotics.

Norman Bel Geddes designed a first electric vehicle, self-driving car which was driven by a radio-controlled electromagnetic fields that are generated by magnetized metal spikes and these spikes are placed in the road. In the year 1958 General Motor’s designed the next version of the car that was created by Norman by embedding the front end of this car with pick-up coils which are sensors that could detect the flow of current through a wire which was embedded on the road. The direction of the vehicle to move was manipulated by the current flow that is to move right or left [26].

Figure 1: Autonomous car by Navlab and AVL [27]

In 1977 a Japanese company improvised this idea by placing a camera in the front part of a car. The data from the car was processed by software but the car could not travel with a speed more than 20mph (miles per hour). Later autonomous car was developed in 1984 in Carnegie Mellon university's Navlab [28]. In later decades Germans designed a car in the form of VaMoRs which could drive safely at 56mph. As the time passed away there were lot if improvements in the design and the technologies that are used in the autonomous vehicles [28].

2.1.2 Impact

The National Highway Traffic Safety Administration (NHTSA) analyses the data across five stages of vehicle autonomy ranging from total human participation to total vehicle autonomy. They divide the autonomous vehicles into 5 levels with level 1 needing the most human interference to level 5 being completely autonomous. In spite of this advancement in technology, the issue of safety still exists. The safety of the passengers is still questionable in vehicles that claim to be fully autonomous. The study explores questions such as will the machine make ethical decisions in events of unavoidable accidents. The decisions that need to be made on the spot of whether to save the passengers or the person/ animal the vehicle has a potential of colliding with. Such issues are what create the fear about safety among consumers of such autonomous vehicles. The manufacturing companies are faced with the ethical dilemma of programming the vehicle with saving more people against the occupants. This will not be a favorable stand for the customers [29].

With the growing technology in this field, the communication systems within vehicles have been on a steady rise. The modern cars are equipped with a lot more safety features with the installation of electronic control units (ECU). There is a prospect of vehicle to vehicle (V2V) communication which could help reduce accidents by creating a link between various vehicles. The cars today are already equipped with autonomous functions such as lane keeping assistance and cruise control. With such advancement comes threat of hackers, the systems controlling the autonomous vehicles can be hacked and so poses a threat to safety. The companies working on this technology need to ensure that the other data collected by these systems if protected. In the past public transport has been automatized such as trams, which were successful. They have the benefits of eliminating human errors and reduce work organization problems. An important advantage of self-driven cars could be that it could provide mobility to people who cannot have a driver’s license like the elderly or disabled population [30].

Self-driven cars have been predicted to help control emission levels and reduce congestion on the roads by ensuring free flowing traffic. Research has found that people prefer conventional or autonomous private cars as a mode of travel. Carsharing has also been a choice which will be highly benefitted from autonomous public transport. With the increase in preference of private car ownership, public transport systems are at a threat of going out a business. A person's age, income and education impact the preference of private car over public transport [31].

This new technology could drive new behavior in the consumers. People could do their office work in the car helping them save some time and leave work earlier. With the comfort people could start considering going on long drives as it reduces the load of driving. This could have a negative impact of increasing traffic on the roads because a lot of people are considering being out more because of not having to worry about driving in traffic. There could be a positive behavior change of people choosing to share the ownership of these autonomous vehicles. This could reduce the number of cars on the streets and in turn increase fuel efficiency. This is a very evolving field and the pros and cons of this technology will keep changing [32] .

2.1.3 Automations in Vehicles

Self-driving cars technology is becoming progressively more common and could drastically transmute our transportation system. There are six levels that are adopted by National Highway Traffic Safety Administration for the automated driving systems. All the vehicles in coming years should classify in one of the Society of Automotive Engineers(SAE) 0 to 5 levels from September 2016. The below diagram gives a complete picture about the 6 types. [33]

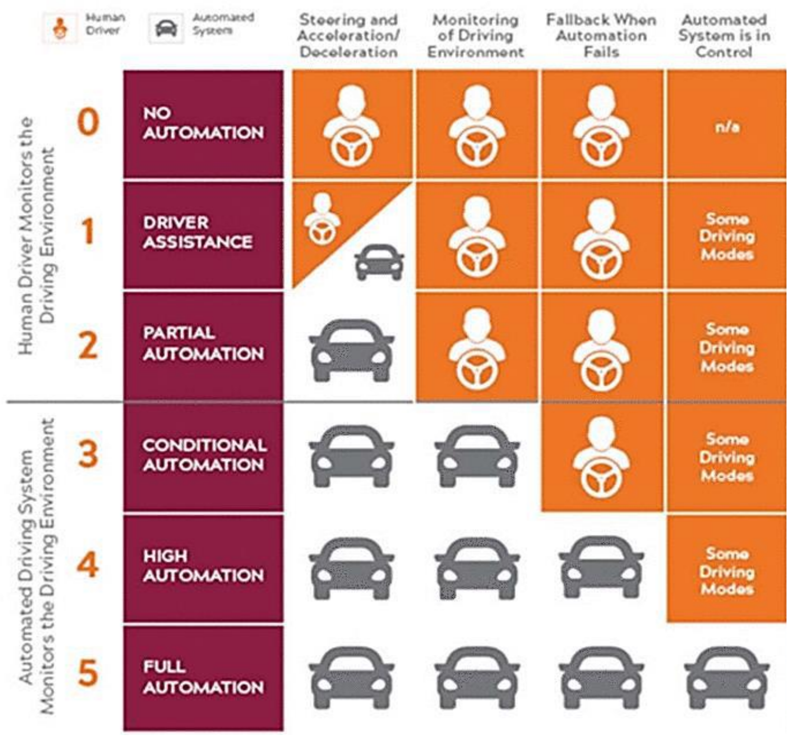


Figure 2: Levels of automation [34]

The Figure 2 shows different levels of automation.

a) Level 0: No Automation

The presence of human is 100 percent(100%) in this level. A human driver is required to operate the vehicle safely at all times. All the controlling tasks like braking acceleration or deceleration or steering are always under human control. Automated Emergency braking is also included in this level [35].

b) Level 1: Driver Assistance

In this level the driver should control all the critical functions. The car cannot control its own operation during any obstruction , etc. In certain modes the car can take the control of steering pedals. It offers smart performance. The parking assistance and the cruise control are the example for this level of automation [35].

c) Level 2: Partial Automation

In this level the driver can cam take his hand off the steering . Few options are available for the driver to control the steering wheel and pedal at the same time. But driver must pay attention and control the vehicle if necessary. Tesla’s Autopilot (2014) is an example for this level [35].

d) Level 3: Conditional Automation

In this level the car becomes the co-pilot. The vehicle manages most of the actions like lane changes, responding to dynamic events, etc. but still human presence in necessary. It is dangerous in terms of liability as it approaches full autonomy.

e) Level 4: High Automation

This level is much safer than the previous level. It does not need any human interference like in other levels. But a functional driver cockpit is still in place. Google’s Waymo cars are the best examples for this level [36].

f) Level 5: Full Automation

In this level the vehicle can be completely driverless. The vehicles are fully automated unlike other levels. The front seats can turn backwards so the passengers can interact more effectively. All the tasks are performed by the vehicle under any circumstances.

This level of automation can totally transform our lives, travels and work. An autonomous driving option are extensive, and they have the most advanced vision, control and detection technologies. They rely on real-time object measurements[33].

Furthermore, the built in information technology is very capable of providing the necessary information both internally (machine) and externally(field) [33].

2.1.4 Basic System in Self-driving Cars

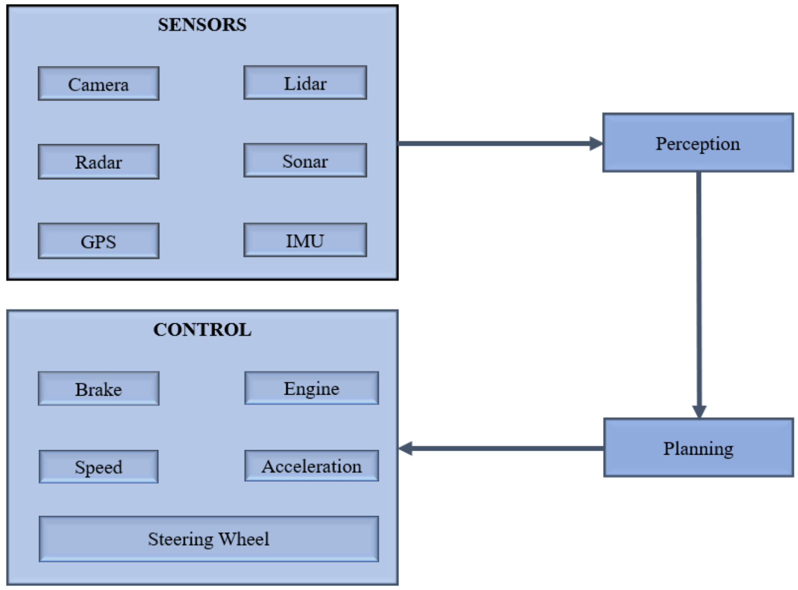


Figure 3: Basic system of Self driving vehicles [37]

The system of autonomous vehicle is divided into four main parts. First part is sensing, the vehicle senses the surrounding environment using different sensors mounted on the it. Then the data collected from the sensor is sent to the perception block, in which the data from the sensors is processed into a meaningful information. Then this information is sent to the planning subsystem. In this stage the behavior planning of action that has to be taken is processed with both long-range and short-range path plan. Now, the subsystem control makes sure that the vehicles follows a safe path that is provided by the before subsystem and also sends the control operation commands that are to be performed by the car.

2.2 Existing Sensor Technologies

An autonomous car is a combination of both hardware equipment and software tools. The combination of various sensors like RADAR, LiDAR and camera may be called a fusion sensor. The sensor in autonomous cars are always observing and these sensors are not affected by the driver's state of mind: angry, moody, sleepy, etc. The research shows that 94% of accidents that take place are due to human mistake. An autonomous vehicle's technologies depend on the capabilities of a car to detect road signs, lane boundaries, signals, unpredicted obstacles and also on the GPS navigation system [28].

A large percentage of the new vehicles in the United States have adapted a technology called Advanced Driver Assistant Systems(ADAS). Use of electronics in modern vehicles are increasing at an exponential rate. Most of the features today are not only related to infotainment but also to support semi-autonomous and moving rapidly to fully autonomous driving.

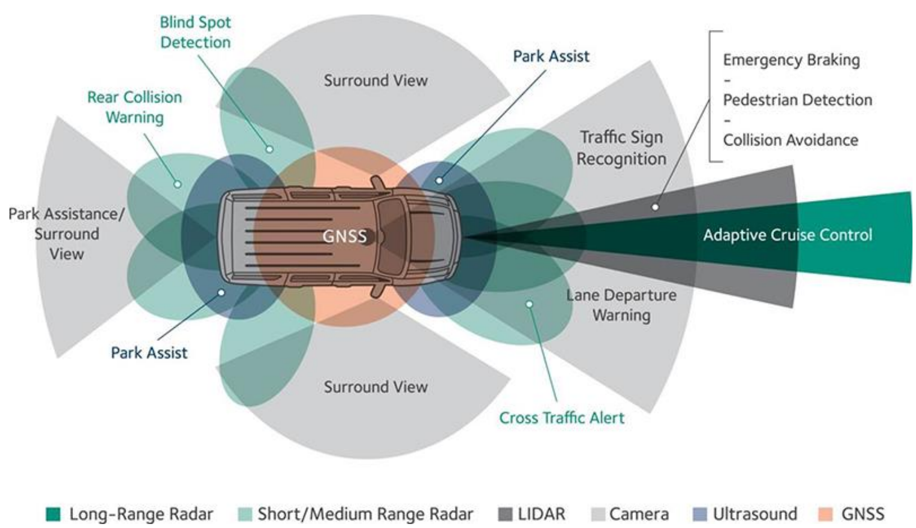


Figure 4: Sensors and their functionality in autonomous vehicle [41]

2.2.1 RADAR

Radio Detection and Ranging(RADAR) is a detection system that is used to detect the objects. By using RADAR, the objects angle, distance, location, and velocity can be determined. It is an electromagnetic system. It emits a high frequency signal. Its operation range is Ultra-high frequencies and the microwave part of radio frequency spectrum.

RADAR emits an electromagnetic pulse into the atmosphere. If there are any targets or objects or any other obstacles the pulse scatters most of the energy, but some part of the signals are reflected to the RADAR receiver. All the scattered signals form a stronger signal if there are more obstacles. From the signal received the direction, altitude and range(distance) can be measured.

Radars have become traditional equipment in superior cars. In the future they are expected to become more common in all car ranges. An increase in safety and assisted driving is possible through radars. Radars are implemented in semi-autonomous cars for either automatic cruise control (ACC) or blind-spot detection (BSD) [39].

Radars in self driving car applications use long-range radar(LLR) systems(80mm to 200m range) which operate in 77GHz frequency band and short-range radars which operate in 24GHz. This frequency band range 76Ghz - 81Ghz are mainly used for improved target resolution, wide band width and also improved accuracy [40].

Radar sensors are located in the front and in the back of the vehicle. These can be used during the low visibility that is during night. Like cameras, radar can also detect an object present around it in all angles. A radar and camera are enough for semi-autonomous vehicles. The radars can determine the speed and distance, but they cannot differentiate the types of vehicles.

Figure 5: RADAR system in cars [41]

2.2.2 LiDAR

LiDAR (Light detection and Ranging) is a remote sensing mechanism that is used in detecting objects using light. The basic principle of a LiDAR is to send laser light to capture and measure the distance from the object. LiDAR's are used extensively in various fields like Autonomous vehicles, Agriculture, Astronomy, Surveying, Healthcare etc. LiDAR's are classified into two types. They are: Orientation based LiDAR's and Platform based LiDAR's. Autonomous vehicles use orientation-based LiDAR's. The localization sub system assesses the position and orientation of the autonomous vehicle. The localization methods are organized into three types: LiDAR-based, LiDAR plus camera based and camera based [42].

In the year 2007, the DARPA Urban Challenge was conducted to test how fully autonomous vehicles reacted to other autonomous vehicles and obstacles merging into traffic, through a competition. This challenge was revolutionary as it was the first-time autonomous vehicles have networked with both manned and unmanned vehicles. The competitors had to follow rules like functioning in rain and fog, traffic light detection, avoid accident with other objects, function in parking areas, stop, stare and perform U-turns. 64-beam rotating LiDAR's were used with high precision. High-resolution maps were also generated for localization [1].

A high-end Lidar can evaluate multiple ranges per a pulse sent to see rain, transparent surfaces, dust and fences. A high-power laser can reduce the signal to noise ratio, but it can damage the human eye so 905nm laser power is used with low duty cycle [43]. The cost of the laser sensor is very high [38].

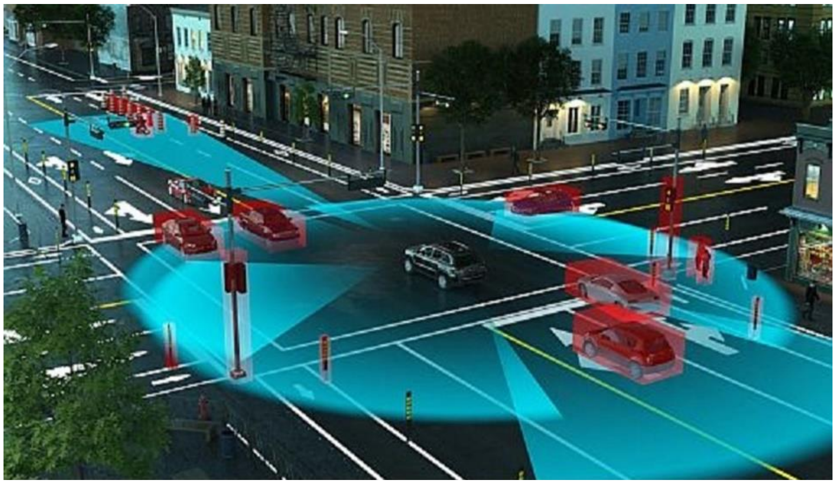


Figure 6: LiDAR system in cars using infrared light [44]

2.2.3 Camera

The cameras are already equipped as back cameras which are helpful while reversing a vehicle since 2018. Autonomous cars and also other vehicle a front facing camera which is used to detect the marking that are painted on the road. The data that is captured for the cameras is fed into the algorithms for classification of objects. Few cameras like infra-red offer visibility and exceptional performance during night or when it is dark.

In Autonomous vehicles multiple cameras: left, right, front and back are placed for a 360-degree view of the vehicle's surroundings. Some cameras cover a range of 120˚ view. The latest high definition camera can generate up to 30 -60 frames per second with millions of pixels per frame [37].

2-D and 3-D cameras require other sensors with very high range. Since the processing rate should be high, other hardware equipment's like FPGA's are used for hardware acceleration. Large storage capacities are used for data compression.

Figure 7: Different cameras view in Tesla's autopilot mode [45]

2.2.4 Other Sensing and Localization Systems

Ultrasonic sensors, Inertial Measurement Unit(IMU) and Global Navigation Satellite System(GNSS) are other sensing and localization systems in autonomous vehicles. These all serve as the other sources of information for the vehicle. For the data received form the different sensors, there should be a computing platform that merges all the data- which guides an autonomous vehicle to take decisions appropriately.

2.3 Vehicular Communication Technologies

Throughout the world, as Internet of Things (IoT) is expanding the automotive industry is also bracing with the changes in both public and individual transportation system. It is estimated that 80% of vehicle accidents can be reduced with the connectivity between the vehicles [46]. Various communication technologies like vehicle-to-vehicle(V2V), vehicle-to-infrastructure(V2I), infrastructure to vehicle(I2V) and infrastructure to infrastructure(I2I) can be employed to enhance communication with traffic lights and increase safety.

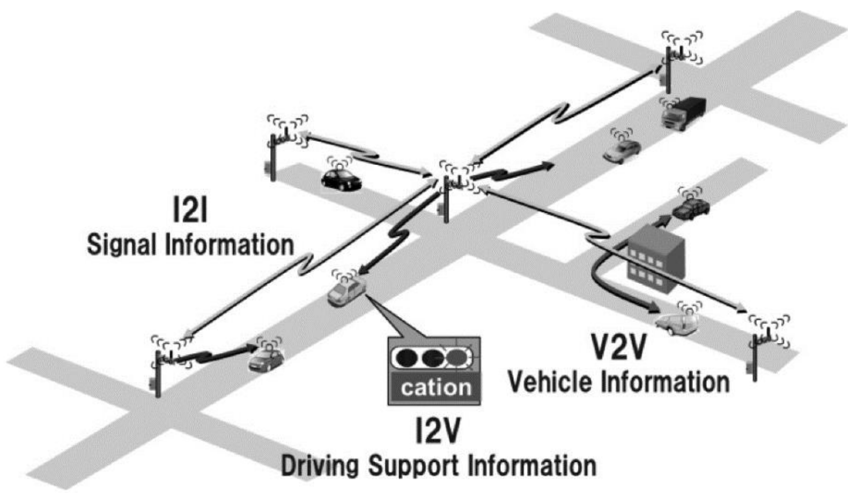


Figure 8: Illustration of V2V, I2V/V2I, and I2I communications systems [47]

2.3.1 Vehicle-to-Vehicle

V2V communication has an ability to exchange wireless information between vehicles. The information like the vehicles position, vehicles speed , etc. within an ad-hoc mesh network can be communicated. This data helps to avoid crashed and ease traffic congestion. There are different topologies through which data can be transferred. Each node is directly connected to the others in first case. And in another case some nodes are connected to all others while only the remaining ones are attached to those where frequent exchange of information takes place. With involvement of different topologies in communication process, the robustness of the network is increased and also the malfunction of the nodes is reduced [48]. The full mesh and partial mesh topologies are represented below.

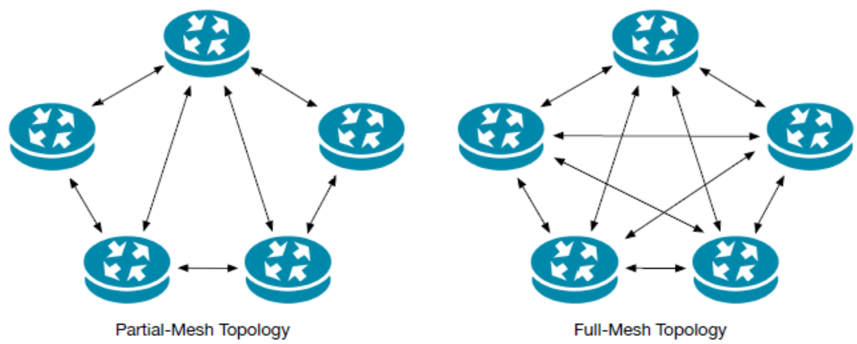


Figure 9: Mesh Topologies [48]

2.3.2 Vehicle-to-Infrastructure or Infrastructure-to-Vehicle

V2I communication acts as an interface between vehicles and road system. The road system consists of components like traffic signals, cameras, parking meters, lane markers, street lamps and RFID readers [49]. This communication is similar to V2V ,bidirectional, wireless, and it uses dedicated short-range communication frequencies for data transfer . The information about roads , parking sites traffic, any accidents and presence of any construction site can be known. The communication with traffic management system help a vehicle to set different speeds according to the traffic flow and also it help in saving fuel [48].

2.3.3 Infrastructure-to-Infrastructure

I2I communication is used for the enhancement of signal control. I2I can be carried out on a same roadside device. The traffic signals present on the same road communicate using I2I communication. The signals can be controlled for giving way to emergency vehicles. The prediction of incoming traffic can be done and then control the signal to allow a particular number of vehicles pass through the intersection. And it is also involved in diverting the traffic during disasters [47].

2.3.4 Communication Protocols

The communication protocol of two or more entities of a communication system to transmit information with a set of rules that describe the syntax, synchronization, and error detection. These communication protocols can be implemented using hardware, software, and both. For V2V communication, proper communication protocols are used for information exchange. V2V uses a wireless protocol similar to WIFI called dedicated short-range communications(DSRC). The DSRC combined with GPS technology provides a 360˚ view of similarly equipped vehicles within range. The communication protocols used in vehicular communication are : IEEE 802.11p, IEEE 802.15.4/ZigBee, Bluetooth and LTE-V2V standards are used [48].

The Wireless Access in Vehicular Environments(WAVE) is introduced by IEEE 802.11p standard. This standard provides multi-channel DSRC. This communication protocol is used in V2V AND V2I communications. The data range from this protocol is 6Mbps to 27 Mbps at a short distance of 300m. The IEEE 802.11 can be implemented in Inter Vehicular Communication(IVC) systems with low data rates [50]. This standard is used in the physical layer. In the physical layer, the WAVE has seven channels. The seven channels are divided as: four channels as service channels, one as a control channel , one high-power long-range channel, and one safety channel. The WAVE channels have 10MHz bandwidth for each channel. The valuation of this standard was done in different circumstances and it was observed that the performance was not satisfactory on the highways. Due to this there will be an increase in packet loss and delay. Similar to IEEE 802.11p, the IEEE 802.11b is used with a communication range of 520 meters [50].

The cellular technologies were used as an alternative to the IEEE 802.11 protocol. The cellular technology like third degeneration partnership project is used to distribute messages efficiently over a large area. The third-generation cellular technologies have long-term Evolution(LTE) and universal mobile telecommunication system. The LTE has range up to 100km, a latency less that 5ms , a downlinking rate of 300Mbps and uplinking rate of 75Mbps [48]. The protocols are mainly used to increase the transmission range, allow proper communication, to reduce the connection time, proper operation during high vehicle density and high mobility conditions [48].

2.4 Basic Algorithm of Self-Driving Cars

The prototype of an autonomous vehicles consists of basic algorithms od image analysis, information storage or data storage and decision-making algorithms. The count of the algorithms used in autonomous vehicles depends on the accuracy , and other computational capabilities [51]. These factors depend upon: RADAR, LiDAR, camera, GNSS, etc. Algorithms can be categorized as:

2.4.1 Environment Recognition with Camera Image

The traffic lane or road recognition, image segmentation and environment-based mapping using visual Simultaneous Localization and Mapping(SLAM) are used in this section of algorithm. The vanishing point method proposed by C. Rasmussen calculates the dominant features in image segments [52]. The identification of objects can be carried out using machine learning algorithms like Full Resolution Residual Networks, Viola-Jones method, Support vector machine method, AdaBoost method, Bag of visual words and other like Genetic algorithms etc. And neural network algorithms, deep learning algorithms like Virtual Generalizing Random Access Memory Weightless Neural Networks, Probabilistic Neural Networks, Convolutional neural networks(CNN) ,etc. SLAM helps in determining the precise position relative to the surroundings. [51].

2.4.2 Environment Recognition with Sensors

There are various SLAM algorithms for RADAR, LiDAR. Graph SLAM and Real time Radar SLAM are the examples of SLAM based Radar algorithms.[53] Maximum SLAM, Credibilist SLAM, Googles Cartographer SLAM can be categorized under lidar based SLAM algorithms [51].

2.4.3 Detection and tracking of moving objects(DATMO)

DATMO algorithms can be implemented on camera, RADAR, LiDAR images. The dynamic objection recognition can be done using the DATMO algorithms by ignoring the SLAM algorithms. But for moving object detection SLAM algorithms serve better that DATMO algorithms in terms of positions, global speeds and to estimate trajectories [51], [54].

2.4.4 Planning and Decision Making

An unusual event may occur any time on the road and can create problems which should be resolved in a peaceful and safe manner. Route planning algorithms like Bellman- Ford algorithm, Dijkstra algorithm and A* algorithm with modification can be implemented [51].

For planning and control of the vehicle, traditional methods like model predictive control, feedback- feedforward control, non-linear control and other end to end method can be used [55] .

Decision making can be done based on considering a number of criteria's. There are no particular classification algorithms of this case. But some of them may be based on Partially Observable Markov Decision Processes , decision trees , Support Vector Machine Regression, Markov Decision Processes, Deep Reinforcement Learning [51].

Artificial Intelligence can be implemented in traffic planning , control and decision making, detection, identification, tracking and also in environmental mapping and other condition as discussed in this section. End-to-end autonomy was implemented in the year 1989 and deep learning(CNN) was used by NVIDIA [51]. Imitation learning techniques are becoming popular these days to learn networks based on images [56] .

2.5 Limitations of Existing Technologies

Self-driving cars will surely make our life easier. But all the predictions that were made earlier were proven wrong like it is easy to achieve level-5 automated driving. Driver less cars will surely make our road safer, but there should be presence of humans behind the steering at least for few years until the level-5 automation is achieved . Many recent incidents gave a clarity that the technology in self-driving cars should be improved more in order to a achieve a driverless vehicle. The autopilot mode in a flight functions because the airspace is a extremely controlled environment. Similarly, the railways have their exclusive tracks. But cars use roads to travel and they operate in a highly complex environments.

The driverless cars are struggling over the bridges. A car is generally fed with the mapped roads so that the driverless car can compare with what it is seeing and what has to be there. When a normal road in urban areas is considered it has many distinguished features like buildings, pedestrians, etc. but when a bridge is considered it does not have many environmental cues to figure out the differences. A regular GPS system only helps car to position itself.

The climatic conditions like snow, heavy rain, etc. can confuse a LiDAR. When there is snow it is difficult for a LiDAR to detect the lane markings that help an autonomous car to drive safely. Ford company could somehow overcome the problem where the car uses landmarks to pinpoint itself on the map [57].

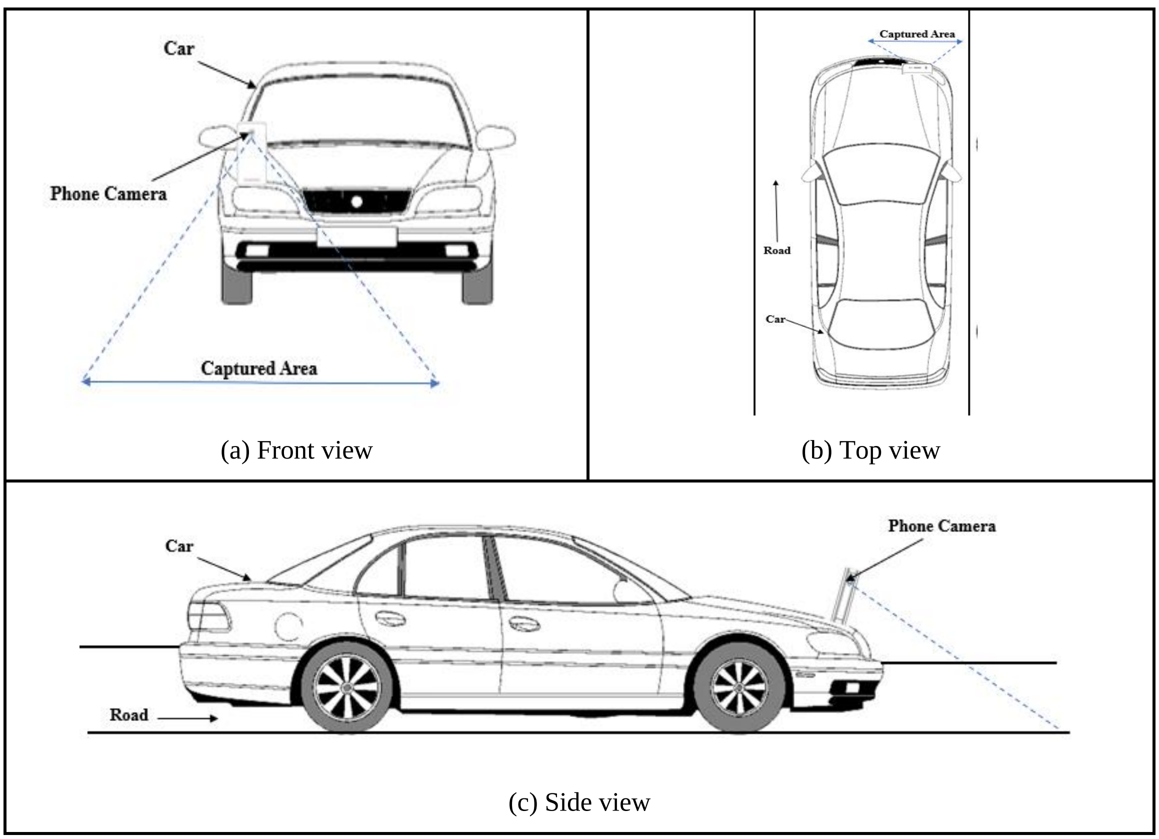
The deep learning algorithms have been implemented in autonomous vehicles successfully. The existing mechanisms for detecting the object, water, pedestrians, etc. depend upon the labeled test data or ad hoc. Sometimes it is still vulnerable is the unexpected behaviors occur and this may lead to collision [58].

3. COLLECTION OF DATASET

3.1. Measurement Setup System

A classification system has a collection of extracted features from the images trained. A large dataset of images is required to train the network. The collection of an image data set has a set of images that were not selected randomly and not imported from any of the existing libraries. This research solely concentrates on the images of the road while the existing libraries have included both the road and its surroundings, so the images were not imported from the existing libraries.

The measurement setup system consists of a car and a mobile phone with a camera. The phone/camera is mounted on a car. The camera is placed at an angle of 75° with respect to the flat surface.



(a) Front view (b) Top view

(c) Side view

Figure 10: Measurement setup system

From Figure 10 , the measurement setup can be seen in three different views: front view, top view and side view. In all the views, the area the camera captured can be observed.

The mobile phone used for this algorithm is iPhone X. It has a dual camera with 12Mega Pixel (MP). It has different features like Quad-LED dual-tone flash, HDR (photo/panorama), panorama, HDR. All the images captured are by default histogram equalized in mobile camera.

3.2. Scenario Description

The images taken from a car of the road surface with and without water are to be captured for image classification. The images were taken from a moving car with the help of a mobile camera aimed in a particular direction. The selected driving path is in the city of San Marcos, TX.

The selected route has roads in different conditions. For example, a road with bike path, a road with few damaged parts, a road with few patches, etc.

From Figure 11, the illustrations of different road conditions can be observed. In Figure 11(a) the road has different patches, Figure 11(b) the road is damaged and Figure 11(c) the road has a bike lane. In this way different road conditions are taken into account.

(a)

(b)

(c)

Figure 11: Different road conditions

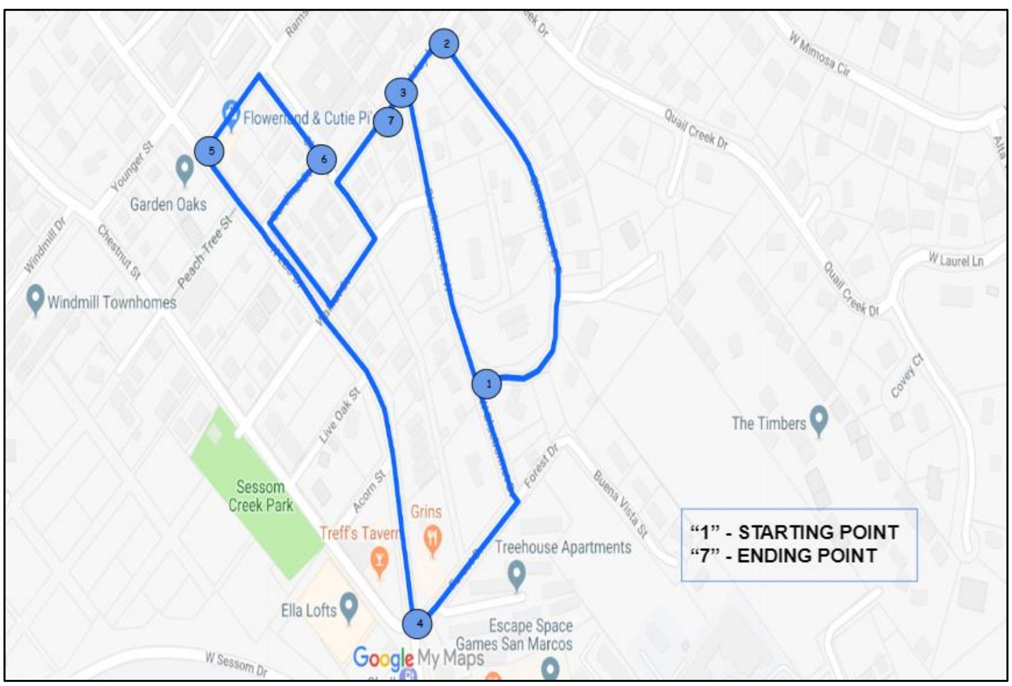


Figure 12: Route map for captured images

A specific route was chosen to capture the images. Images were collected during three different climatic conditions: sunny, rainy and cloud. A count of 100-120 pictures are taken under each condition and the best 96 images from each condition were considered. The route map area is shown in figure 12.

In the map, the starting point is at ‘1’ and the ending point is ‘7’. The considered path has different types of road: primary streets, esplanade, etc.

(a) (b)

(c)

Figure 13: Different street views

The Figure 13 shows the different types of roads that were considered to capture images taken from Google Maps. The Figure 13(a) shows the road from point 4, Figure 13(b) shows the road from point 5 and Figure 13(c) shows the road from point 6 which are mentioned in Figure 12 can be observed. In this way different road conditions are considered.

3.3. Climatic Conditions for collection of data

There are various climatic conditions are considered for capturing images. All the images were captured at the same place on the same roads in different climatic conditions to get proper accuracy. The different climatic conditions are categorized as Rainy, Cloudy and Sunny. Since this experiment is for testing if there is water present on the road or not, these various climatic conditions are considered. Water is present only in one of the three conditions. A count of 100 -120 pictures were taken under each condition.

3.3.1. Condition 1 – Rainy

For this condition, the pictures were shot in 69˚F in the mentioned route figure displayed in section 3.3. For example, few pictures are shown below. In this section water is present.

(a) (b) (c)

Figure 14: Examples of images captured for rainy condition

From the images in Figure14, it can be observed that these pictures were captured after rain and also there is water.

3.3.2. Condition 2 – Cloudy

For this condition, the pictures were shot in 68˚F in the mentioned route figure displayed in section 3.3. The sky was partially cloudy. For example, few pictures are shown below. In this section there is no presence of water.

(a) (b) (c)

Figure 15: Examples of images captured for cloudy condition

From the images in Figure 15, it can be observed that these pictures were captured when it was partially cloudy and also there is no water.

3.3.3. Condition 3 – Sunny

For this condition, the pictures were shot in 76˚F in the mentioned route figure displayed in section 3.2. For example, few pictures are shown below. In this section there is no presence of water.

(a) (b) (c)

Figure 16: Examples of images captured for sunny condition

From the images in Figure 16, it can be observed that these pictures were captured when the sky is clear , sunny and also there is no water.

3.4. Processing images

The images in the data set have different categories of images. From all the images only, a particular part is cropped. So before training the images into the data base, the images are cropped to remove the unnecessary noise since this research only concentrates on road. All the images are cropped manually.

Example: 1

(i) Original Image (ii) Selected part (iii) Cropped Image

(a)

Example: 2

(i) Original Image (ii) Selected part (iii) Cropped Image

(b)

Example: 3

(i) Original Image (ii) Selected part (iii) Cropped Image

(c)

Figure 17: Preprocessed images

The above figures, Figure 17 (a), (b), (c) are the examples of image preprocessing where a particular part of an image is selected and cropped. In (i) from the above listed examples, the original captures image is presented, in (ii) a particular part of image that is to be cropped is selected and in (iii) the cropped image part is display. Since only the road part in an image is the requirement , the other parts are removed in all the images captured.

4. IMAGE CLASSIFICATION ALGORITHM

Image classification system consists of a different categories of data, feature extraction block, database to collect the features from an image.

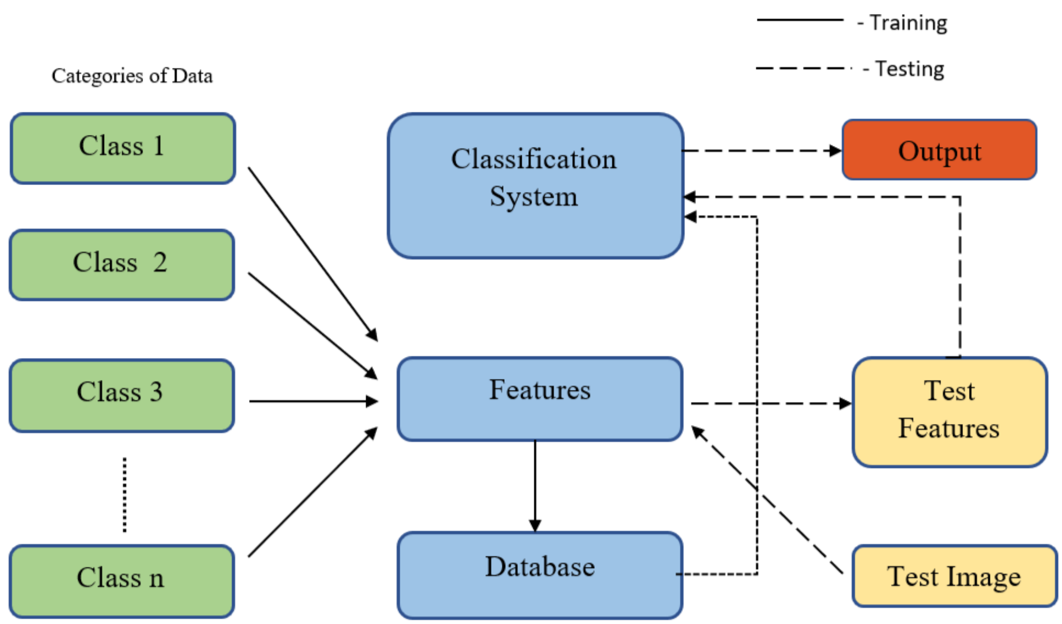


Figure 18: Image Classification System

From Figure 18, the categories of data have different class instances. The features from all the images from are extracted and stored in a database. The extracted features: mean and standard deviation are store in the form of values. These values are stored in the classification system and are used while testing an image for its class.

A test image is given as an input to the network for testing, the features are extracted and are stored as test features. These test features are compared with the feature values that are present in classification system. The classification is done based on the minimum distance and the category to which the test image belongs to is displayed as the output.

4.1. Image Classification Algorithm for Grayscale Images

The algorithm has two main parts: training and testing of images. This image classification algorithm is trained with grayscale images.

4.1.1. Training Algorithm for Grayscale Images

4.1.1.1. Training Algorithm

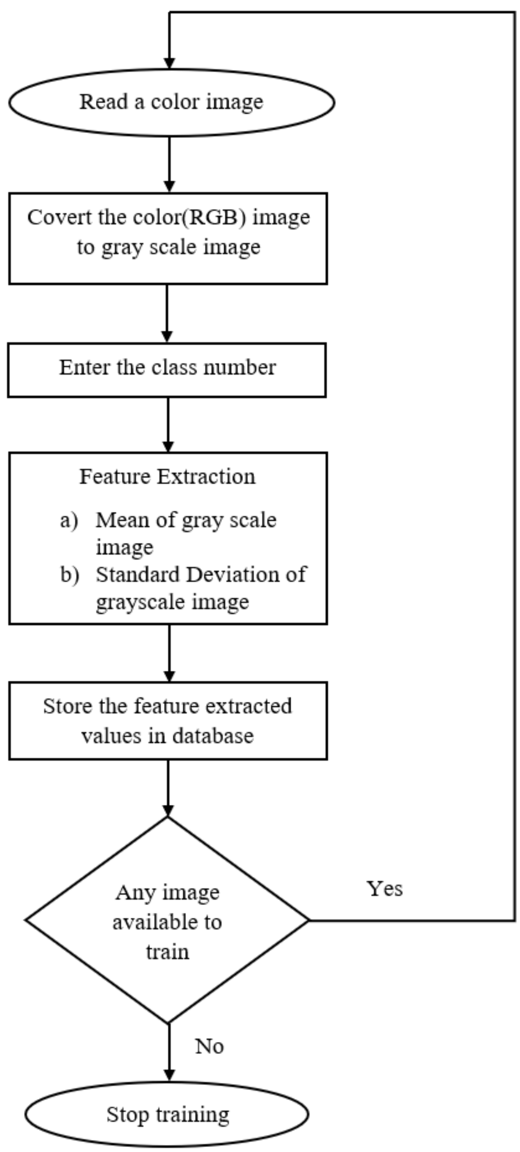


Figure 19: Training algorithm for gray scale images

In Figure 19, the step by step process of training an image can be observed. First an image that is to be trained is given as input or its path is given as input. The preprocessing of an image: converting color image to gray. The size of an image is decreased in order to reduce the space occupied by a picture. The image after preprocessing is displayed.

Once the image is preprocessed, then class of an image has to be entered. The class of an image is the category to which the input image belongs to. There may be number of images, the images of same type come under a single class. In this way there may be any number of classes.

The extracted image's features: mean and standard are extracted in the next process. The feature extraction block has multiple tasks to be performed. A double precision array is created, and the values of standard deviation and mean are calculated. These calculated values of mean and standard deviation are stored in a database in the form of a matrix. The matrix is appended with the class name. so now the matrix has all features extraction values and the class numbers.

The database consists of all the values of an image that are stored in a matrix. When the images are trained continuously that values in the database are added one after another. Once are the images from all the class are trained, then the training process ends else the same process continues.

4.1.1.2. Training Process

a) Read an image

In the first step of the training process the image is selected image is read from the path. The selected image for training is displayed below.

Figure 20: Input Image for training

b) Preprocessing an image

The input image is converted from color to gray image. The input color image has three channels: red, green and blue. The color image is converted by using “rgb2gray” MALTAB function. The figure 21 represents the converted gray scale image.

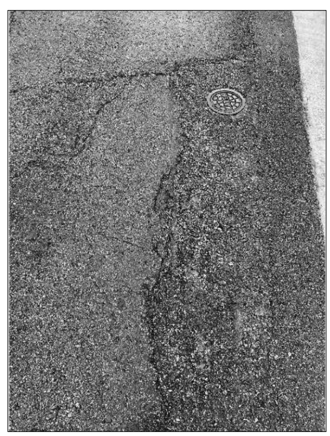


Figure 21: Input RGB image converted to gray scale

c) Class of an image

There are various images from different categories. So, different categories are assigned with different class numbers. The class number of an image is given with respect to the category it belongs to: rainy(1), cloudy(2) and sunny(3). The image resizing and the color image is converted to gray in the preprocessing block of this algorithm.

d) Feature Extraction of an image

An image has various features. The mean gives aggregate value and the contributions of individual pixel of an image that cannot be seen, and the standard deviation of an image is the measure of variability of image pixels. Low standard deviation is the indication of closeness of all the pixel values to the mean and high standard deviation indicates all the values are spread out. The features like standard deviation and mean are concentrated. Once the class number is given and mean, and standard deviation are calculated, these values are stored in a database in the form of a matrix.

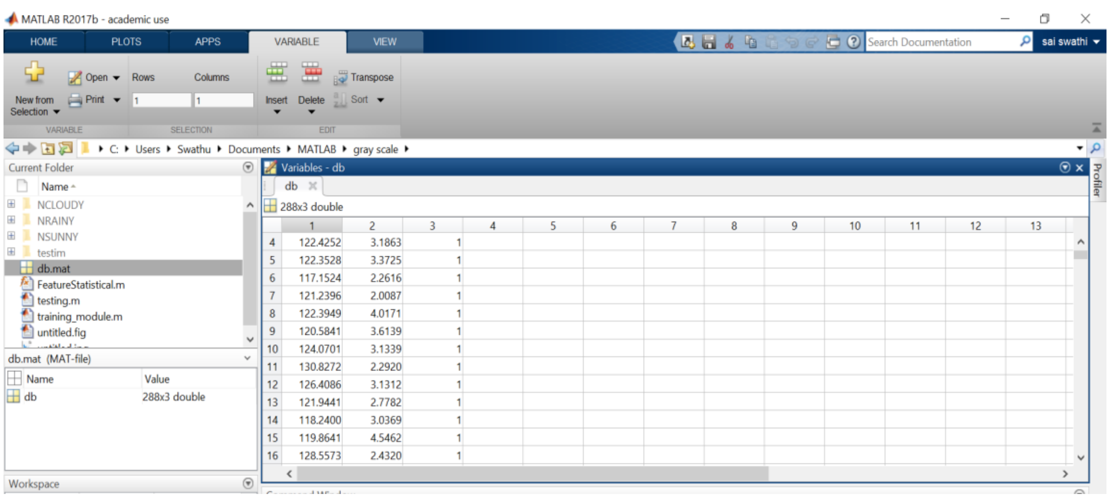


Figure 22: Stored values of trained grayscale images in database

From the figure 22, the matrix "db" has three different columns. The "db" represents database. The first column represents the mean values of grayscale trained images, second column represents the standard deviation values of trained grayscale images and the last column- third column represents the class number: 1 for rainy climatic condition, 2 for cloudy climatic condition, and 3 for sunny climatic condition.

There are a total of 288 images considered where 96 from each category are trained after preprocessing.

The training process of a single image ends here. Similarly, if there are any other images, the same process continues, and the class number is given according to the category to which the image belongs to.

4.1.2. Testing Algorithm for Grayscale Images

In figure 23, the step by step process of classifying an image(testing) can be observed. First an image that is to be tested is given as input or its path is given as input. Then the image is preprocessed. The preprocessing of an image: converting color image to gray.

The preprocessed image's features are extracted. The feature extraction block has multiple tasks to be performed. A double precision array is created, the values of standard deviation and mean are calculated. These calculated values of mean and standard deviation are stored as test features because an image cannot be directly compared with another image. Some values for classification should exist.

The mean and standard deviation are features or parameters that the extracted from the trained images. The image classification has to be performed based on these features. From the plots of mean and standard deviation discussed in section 4.1.3.1 for different climatic conditions, it can be observed that the values of standard deviation and mean almost lie in the same region.

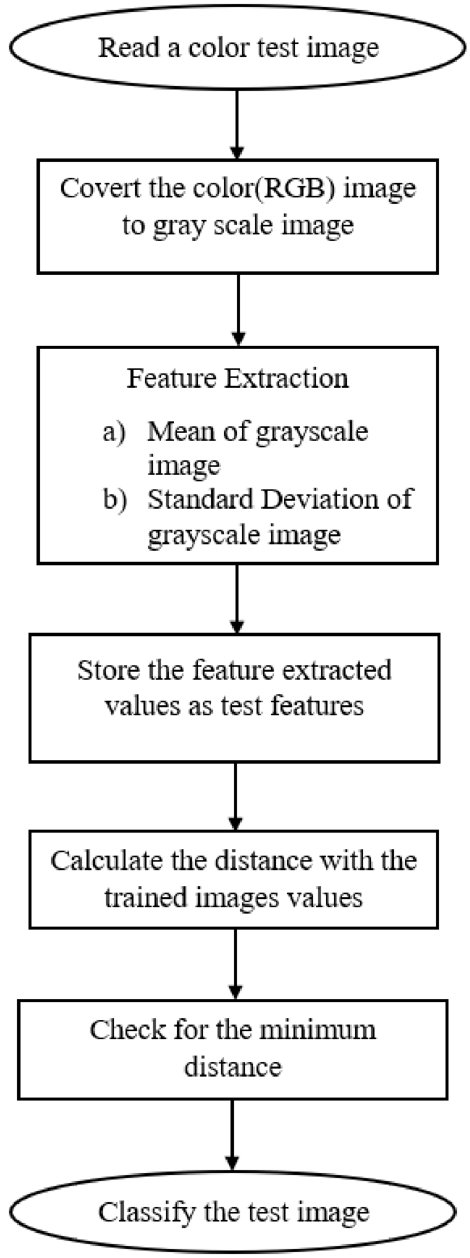


Figure 23: Testing algorithm for gray scale images

The standard deviation values or the mean values are not considered alone. The difference between these two parameters is considered. These two values are stored in the form of a matrix. Let, I_{train} has the mean (μ_m) and standard deviation (σ_m) values of an image in trained set for classification and $\mathrm{I}_{\mathrm{test}}$ has the mean(μ_x) and standard deviation(σ_x) values of a test image. The matrices of I_{train} and I_{test} are represented below.

$$I_{test}^{n\times2} = [\mu_x \quad \sigma_x], \quad I_{train}^{m\times2} = \begin{bmatrix} \mu_1 & \sigma_1 \\ \mu_2 & \sigma_2 \\ \vdots & \vdots \\ \mu_m & \sigma_m \end{bmatrix}$$

Where, n = 1 and m = 288

From the above matrices, the ' n' value of the text matrix is always 1. The testing of only one image is done at a time so n value is 1. The value of m is equal to the number of images trained. In this case the number of images trained is 288.

The distance is calculated by considering the values of a trained image (μ_m, σ_m) and the test image (μ_x, σ_x). This value is stored and then the same continues till the 288th trained image $(\mu_{288}, \sigma_{288})$ and the test image is same for all the cases. The Distance(D) is calculated by taking the sum of absolute difference between the values of mean and standard deviation respectively. The distance (D) is given by,

$$\mathrm{D} = \mathrm{sum}(\mathrm{abs}(I_{train} - I_{test}))$$

The above equation can also be written as,

$$\mathrm{D}_1 = (\mathrm{abs}(\mu_1 - \mu_x) + \mathrm{abs}(\sigma_1 - \sigma_x))$$

$$\vdots \qquad\qquad \vdots$$

$$\mathrm{D}_m = (\mathrm{abs}(\mu_m - \mu_x) + \mathrm{abs}(\sigma_m - \sigma_x)) \qquad - (1)$$

The classification of a test image is done based on the minimum distance between the value of the distances(D) stored. The equation 1 represents the distance calculated for single color channel. The minimum distance(J) from the stored distances values. The minimum distance(J) is given by ,

$$\mathrm{J} = \mathrm{argmin}([\mathrm{D}])$$

Notation

Parameter	**Definition**
μ_m	Mean value of trained images
μ_x	Mean value of test image
σ_m	Standard Deviation value of trained images
σ_x	Standard Deviation value of test image
I_{train}	Values of mean and standard deviation of a trained image (μ_m, σ_m)
I_{test}	Values of mean and standard deviation of a test image (μ_x, σ_x)
D_m	Distance(D) between a 'mth' trained image and a test image
[D]	288x1 Matrix with the distances between a test image and 288 trained images

The test feature values are compared with the trained images features that are in classification system which has all the values from database. The classification of an image is done based on the minimum distance between the feature values. Since there is water present in only in the rainy climatic condition and not in other conditions: sunny and cloudy, the algorithm give output as water if class 1 is detected and no water if either class-2 or class-3 is detected. The output is displayed as water or no water.

4.1.3. Results for Grayscale images

The results section of image classification through grayscale images has two parts: histogram plots of mean and standard deviation and the testing process.

4.1.3.1. Histogram plots

The values of mean and standard deviation are represented in the histogram plots.

a) Mean

The mean of the images under three different conditions are plotted below. When an image is captured from a mobile camera, the image's brightness is compensated and also the it is histogram equalized as it is the default feature of the camera. It also masks the original mean values of the image. So, the values of the mean lie in between 110 and 155 and are not widespread.

Condition 1 – Rainy

In figure 24, the frequencies of mean value are plotted for rainy climatic condition. It can be observed that the mean values are distributed, and maximum number of values lie in between 118 and 125.

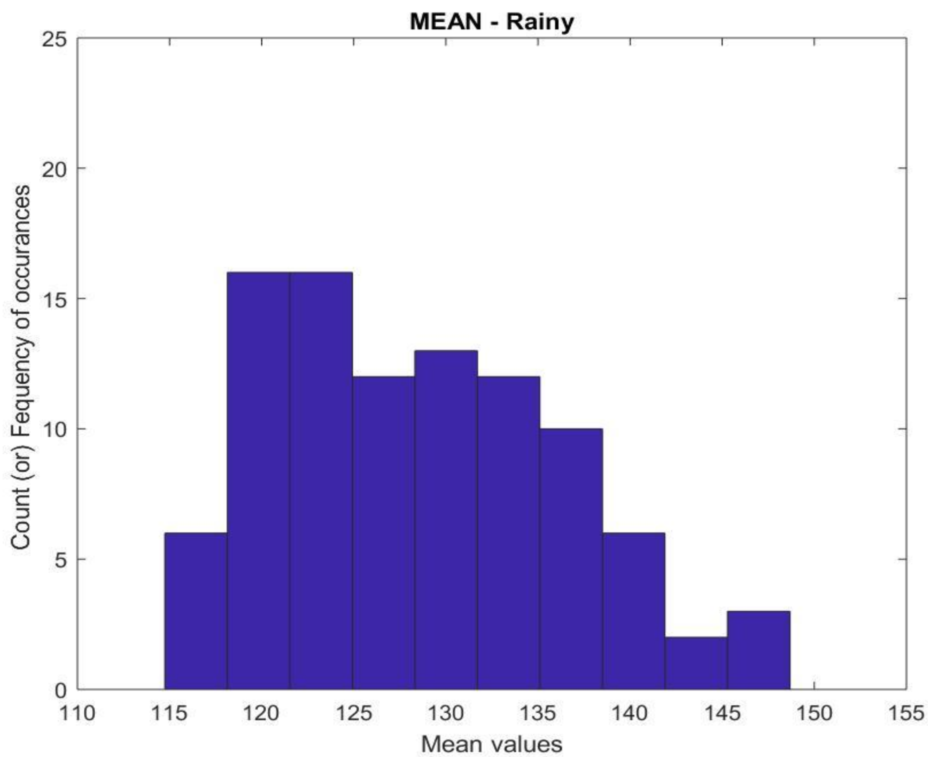


Figure 24: Histogram plot of Mean values – Rainy

Condition 2 – Cloudy

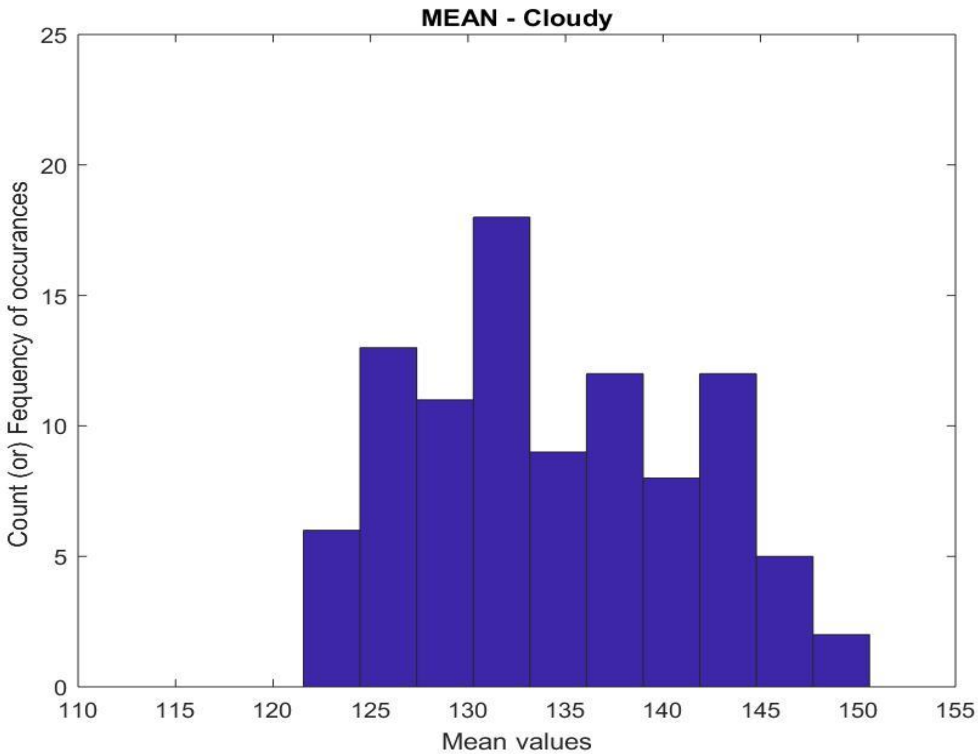


Figure 25: Histogram plot of Mean values- Cloudy

The frequencies of mean values are plotted for cloudy climatic condition in figure 25. It can be observed that the mean values are distributed between 122 and 150. The maximum number of values lie in between 130 and 133.

Condition 3 – Sunny

In figure 26, the frequencies of mean values are plotted for sunny climatic condition. It can be observed that the mean values are distributed between 110 and 148, and maximum number of values lie in between 125 and 130.

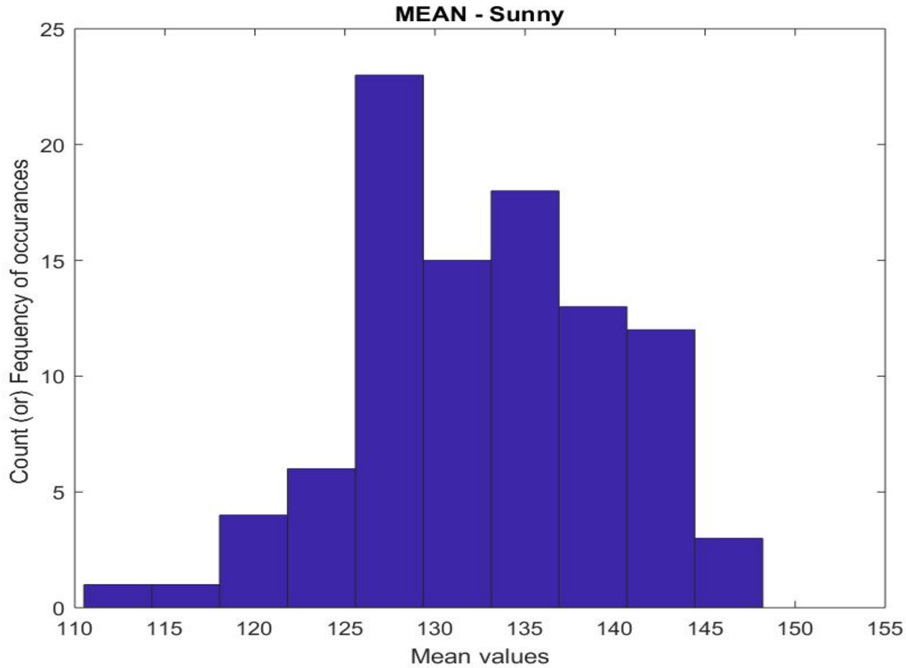


Figure 26: Histogram plot of Mean values- Sunny

From all the above histogram plots of mean values for various climatic conditions it can be observed that the mean values are distributed in between the range 110 and 155. Though the mean values are distributed, the frequency of occurrence of mean values is different for different climatic conditions.

The contribution intensity of the individual pixel values of an image is given by mean. From the above histogram plots of mean , the effect of histogram equalization and the compensation of brightness can be observed since the mean values are not widespread.

b) Standard Deviation

Condition 1 – Rainy

In figure 27, the frequency of occurrences of standard deviation value are plotted for rainy climatic condition. It can be observed that the Standard deviation values are distributed between 2 and 16 but maximum number of values lie in between 2 and 3.

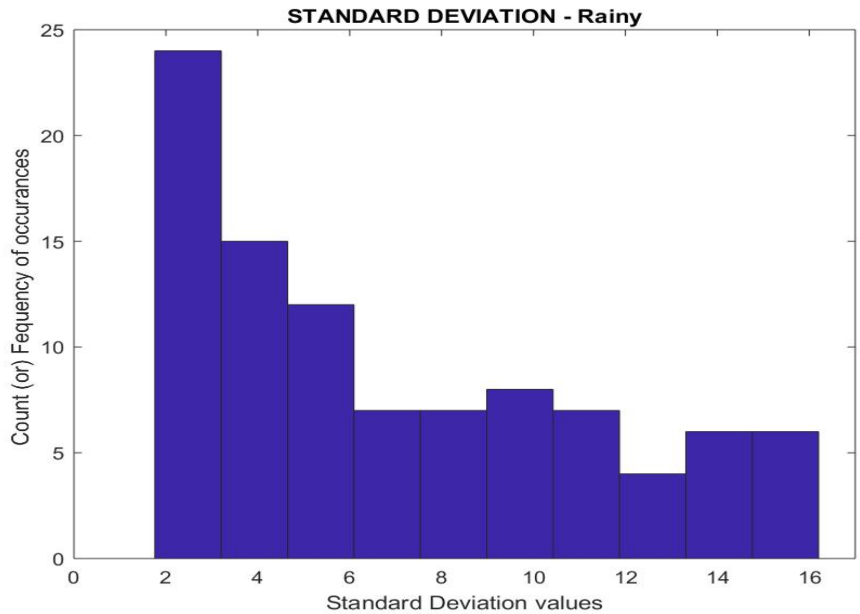


Figure 27: Histogram plot of Standard Deviation values – Rainy

Condition 2 – Cloudy

The frequencies of standard deviation values are plotted for cloudy climatic condition in figure 28. It can be observed that the standard deviation values are distributed between 1 and 14. The maximum number of values lie in the interval 2.

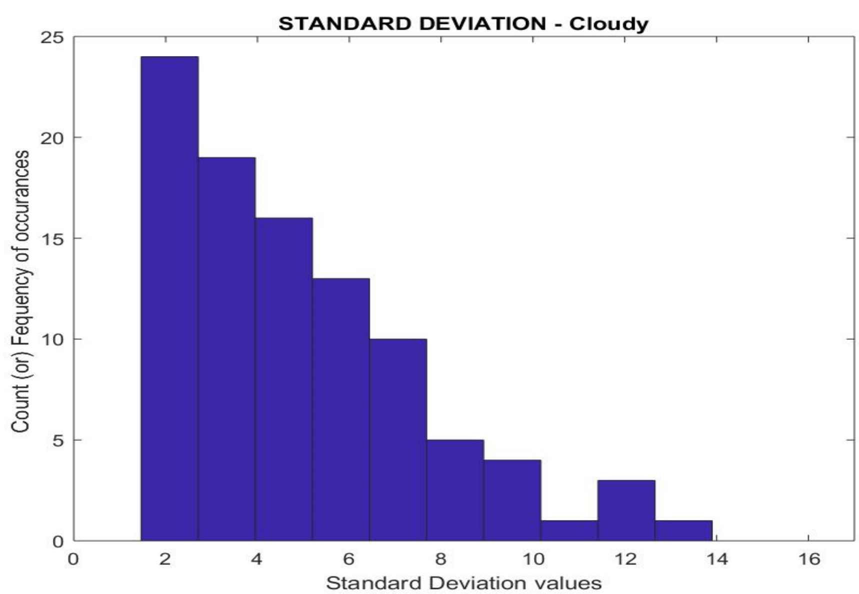


Figure 28: Histogram plot of Standard Deviation values – Cloudy

Condition 3 – Sunny

In figure 29, the frequencies of standard deviation values are plotted for sunny climatic condition. It can be observed that the standard deviation values are distributed between 1 and 14, but maximum number of values lie in between 3 and 4.

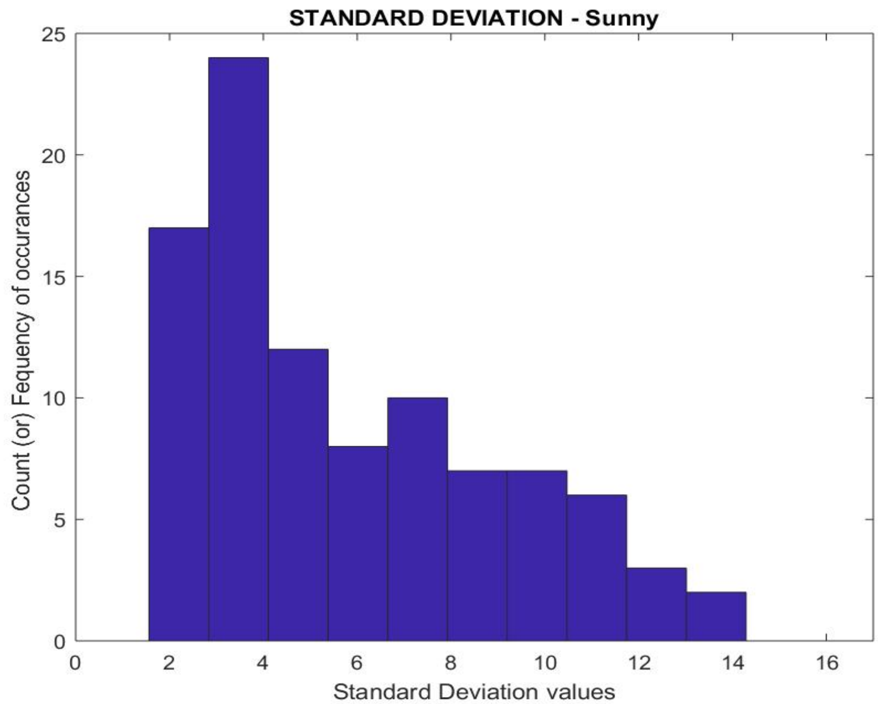


Figure 29: Histogram plot of Standard Deviation values – Sunny

From all the above histogram plots of standard deviation values for various climatic conditions it can be observed that the standard deviation values are distributed in between the range 1 and 17. Though the standard deviation values are distributed, the frequency of occurrence of standard deviation values is almost same that is all the values lie in between 2 and 4 for different climatic conditions.

The amount of variation of the pixel values is given by standard deviation. In all the conditions, the standard deviation value lie in almost similar region because a standard deviation value depends upon the variation of a pixel intensity in an image. In an image if all the pixel values tend to be closer, the standard deviation value is less.

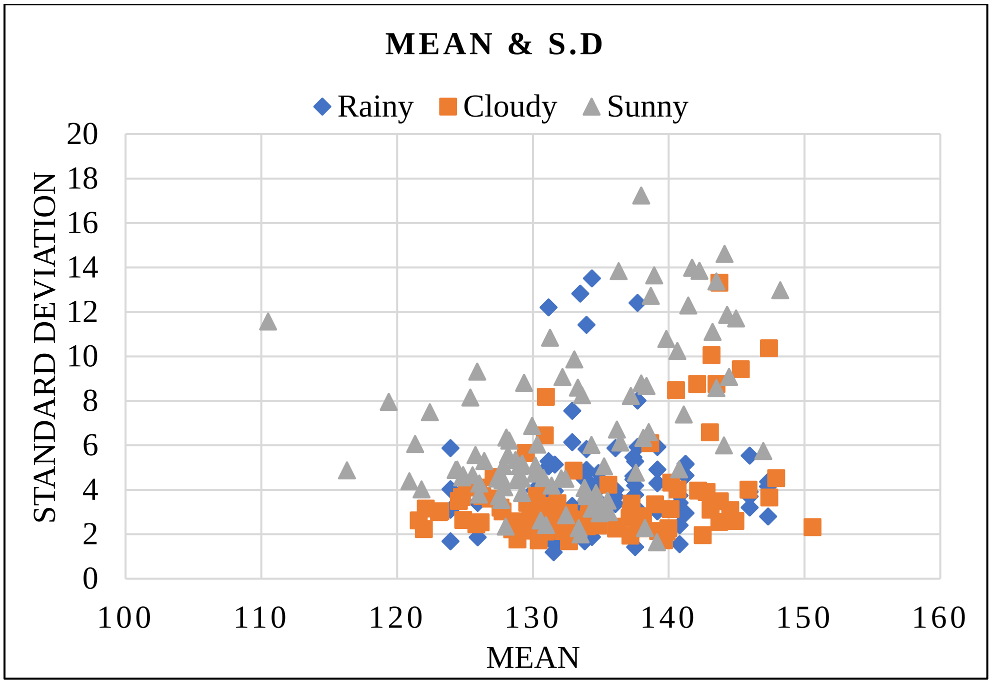


Figure 30: Plot of mean and standard deviation values of different climatic conditions

The values of standard deviation and mean for all three climatic conditions are plotted in the figure 30. From the plot it can be observed that the values of mean and standard deviation overlap on each other. The values did not form any separate clusters to differentiate the climatic conditions. If there were different clusters formed then centroid of each cluster would have been helpful in classifying the images.

4.1.3.2. Testing Process

The testing of an image with respect to training is performed to classify the image's category: water or no water.

The input for testing algorithm for image classification is selected from the other random images but not from the trained images. The test image has no water. The input image is presented in figure 31.

Figure 31: Input color image for testing

The test image is preprocessed before classifying. The test image’s is converted from color to gray image by using “rgb2gray” MALTAB function. The output of a preprocessed image is shown below.

Figure 32: Preprocessed test image

From the preprocessed image features are extracted and are stored as test features. These test features values are compared with the values trained image values in the classification. The output is displayed below.

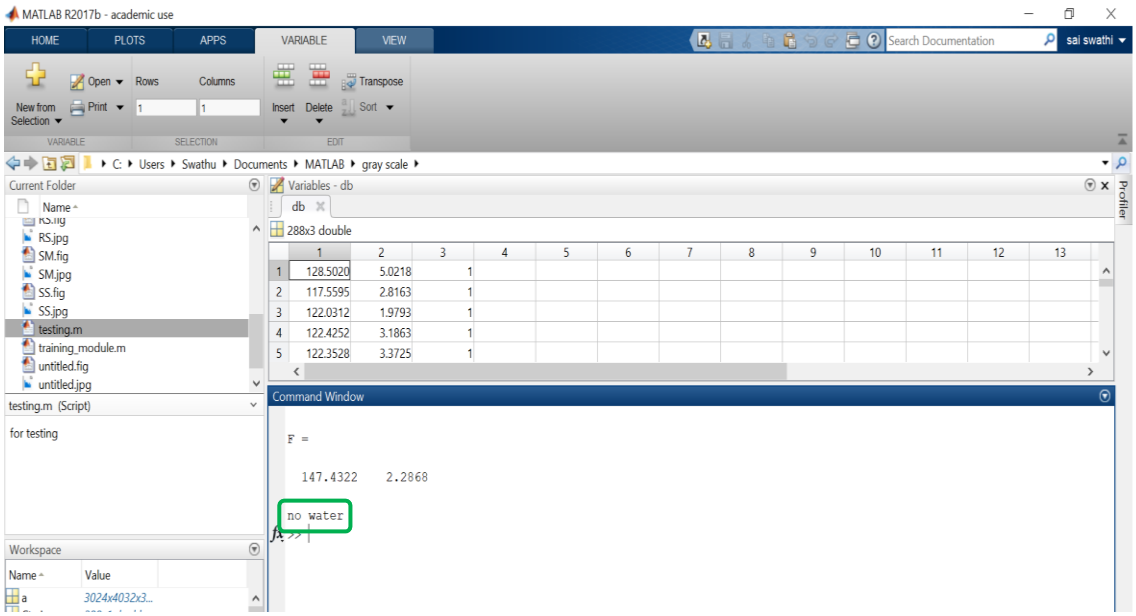


Figure 33: Output of image classification system tained with grayscale images

The test image which was fed to the image classifier had no water and was captured in sunny condition. And now the image classifier classified the image correctly that it has no water. The output image screenshot, Figure 33 has mean and standard deviation values of the test image and the output is highlighted. There are various examples discussed in the section 4.4.1.

4.2. Image Classification Algorithm for Color Images

A similar algorithm for image classification using grayscale images is used for image classification algorithm for color images. The color images have three different color channels: red channel, green channel and blue channel. The algorithm has two main parts: training and testing the color images.

4.2.1. Training Algorithm for Color Images

4.2.1.1. Training Algorithm

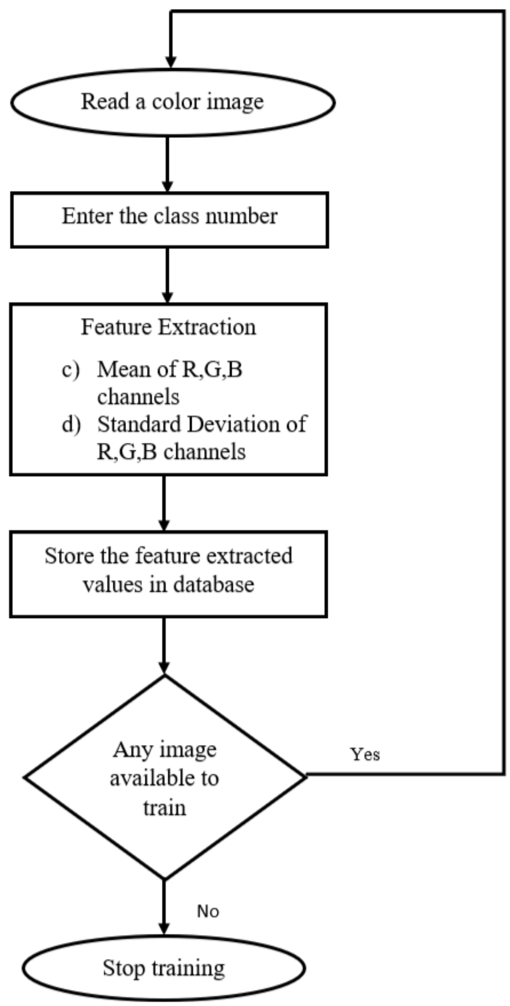


Figure 34: Training algorithm for color(RGB) images

From figure 34, the step by step process of training a color image can be observed. First an image that is to be trained is given as input or its path is given as input.

Once the color image is given as input, then class of an image has to be entered. The class of an image is the category to which the input image belongs to. There may be number of images, the images of same type come under a single class. In this way there may be any number of classes.

The image's mean and standard deviation of three different channels in a color image: red channel, green channel and blue channel are extracted in the next process. The feature extraction block has multiple tasks to be performed. A double precision array is created, and the values of standard deviation and mean for three channels is calculated. These calculated values of mean and standard deviation are stored in a database in the form of a matrix. The matrix is appended with the class name. So now the matrix has all features extraction values and the class numbers. This process continues in a loop till all the images from different categories are trained with respective class numbers.

The database consists of all the values of an image that are stored in a matrix. When the images are trained continuously that values in the database are added one after another.

4.2.1.2. Training Process

a) ***Read an image***

In the first step of the training process the image is selected image is read from the path. The selected image for training is displayed below.

Figure 35: Input Color Image for training

b) ***Class of an image***

There are various images from different categories. So, different categories are assigned with different class numbers. The class number of an image is given with respect to the category it belongs to: rainy(1), cloudy(2) and sunny(3). The image resizing and the color image is converted to gray in the preprocessing block of this algorithm.

c) ***Feature Extraction of an image***

An image has various features. The mean gives aggregate value of the pixels of an image that cannot be seen.. And the standard deviation of an image is the measure of variability of image pixels. Low standard deviation in the indication of closeness of all the pixel values to the mean and high standard deviation indicates all the values are spread out. The features like standard deviation and mean are concentrated. Once the class number is given and mean, standard deviation are calculated these values are stored in a database in the form of a matrix.

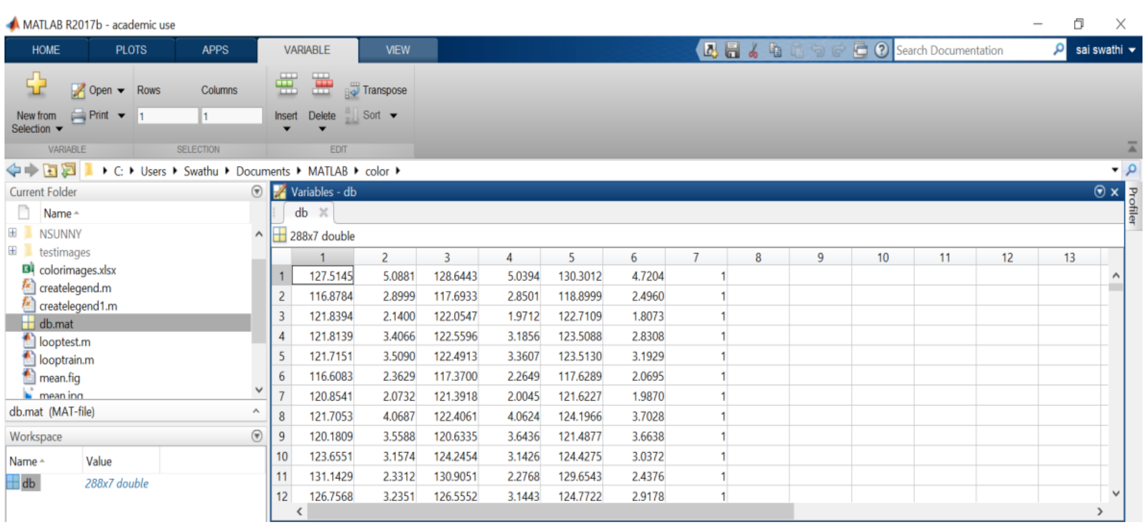


Figure 36: Mean and standard deviation values of trained color images in a database

In the figure 36, the mean values, standard deviation values and the class numbers can be observed. The database “db” has seven columns: the first column represents the mean value of red channel, second column represents the standard deviation value of red channel, third column represents the mean value of green channel, fourth column represents the standard deviation value of green channel, fifth column represent the mean value of blue channel, sixth column represents the standard deviation value of blue channel and the seventh column represents the class number: 1 for rainy climatic condition, 2 for cloudy climatic condition, and 3 for sunny climatic condition. There are a total of 288 images considered where 96 from each category were trained.

The training process of a single image ends here. Similarly, if there are any other images, the same process continues, and the class number is given according to the category to which the image belongs to.

4.2.2. Testing Algorithm for Color Images

The figure 37 represents the step by step process of classifying an image(testing) can be observed. First a color image that is to be tested is given as input or its path is given as input.

The test image’s features are extracted. The feature extraction block has multiple tasks to be performed. A double precision array is created, the values of standard deviation and mean for three different channels are calculated as the input is a color image and there is no preprocessing done. These calculated values of mean and standard deviation are stored as test features because an image cannot be directly compared with trained image.

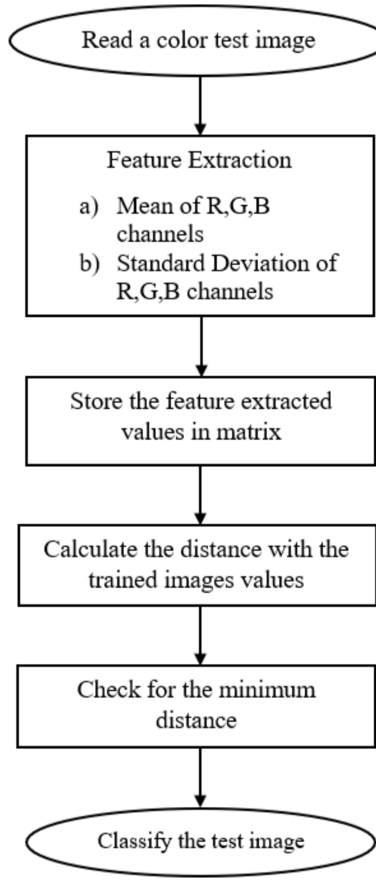


Figure 37: Testing algorithm for color(RGB) images

The mean and standard deviation are features or parameters that the extracted from the trained images. The image classification has to be performed based on these features.

As discussed in section 4.1.2 the mean and standard deviation values are not considered alone. The equation 1 represents the calculation of distance for single channel. But when color images are considered there exists three different channels so the equation 1 is considered as reference and modified for 3 channel. And the parameters considered are similar to equation 1.The difference between these two parameters is considered. The matrices of I_{train} and I_{test} are represented below.

$$I_{test}^{n\times 6} = [\mu_{xr} \quad \sigma_{xr} \quad \mu_{xg} \quad \sigma_{xg} \quad \mu_{xb} \quad \sigma_{xb}],$$

$$I_{train}^{m\times 6} = \begin{bmatrix} \mu_{1r} & \sigma_{1r} & \mu_{1g} & \sigma_{1g} & \mu_{1b} & \sigma_{1b} \\ \mu_{2r} & \sigma_{2r} & \mu_{2g} & \sigma_{2g} & \mu_{2b} & \sigma_{2b} \\ \vdots & & & & & \vdots \\ \mu_{mr} & \sigma_{mr} & \mu_{mg} & \sigma_{mg} & \mu_{mb} & \sigma_{mb} \end{bmatrix}$$

Where, n = 1 and m = 288

From the above matrices, the ‘ n’ value of the text matrix is always 1. The testing of only one image is done at a time so n value is 1. The value of m is equal to the number of images trained. In this case the number of images trained is 288.

The absolute distance between the mean and standard deviation values of the trained I_{train} and test images I_{test} is calculated. The Distance(D) by is calculated by taking the sum of absolute difference between the values of mean and standard deviation respectively. The distance (D) is given by,

$$\mathrm{D} = \mathrm{sum}(\mathrm{abs}(I_{trainr} - I_{testr}) + \mathrm{abs}\left(I_{traing} - I_{testg}\right) + \mathrm{abs}(I_{trainb} - I_{testb}))$$

The above equation can also be written as,

$$\mathrm{D}_1 = (\mathrm{abs}(\mu_{1r} - \mu_{xr}) + \mathrm{abs}(\sigma_{1r} - \sigma_{xr}) + \mathrm{abs}\left(\mu_{1g} - \mu_{xg}\right) + \mathrm{abs}\left(\sigma_{1g} - \sigma_{xg}\right)$$
$$+ \mathrm{abs}(\mu_{1b} - \mu_{xb}) + \mathrm{abs}(\sigma_{1b} - \sigma_{xb}))$$
$$\vdots \qquad \vdots \qquad \vdots$$
$$\mathrm{D}_m = (\mathrm{abs}(\mu_{mr} - \mu_{xr}) + \mathrm{abs}(\sigma_{mr} - \sigma_{xr}) + \mathrm{abs}\left(\mu_{mg} - \mu_{xg}\right) + \mathrm{abs}\left(\sigma_{mg} - \sigma_{xg}\right)$$
$$+ \mathrm{abs}(\mu_{mb} - \mu_{xb}) + \mathrm{abs}(\sigma_{mb} - \sigma_{xb}))$$

- (2)

The classification of a test image is done based on the minimum distance between the value of the distances(D) stored. The equation 2 represents the distance calculated for three color channels. The minimum distance(J) from the stored distances values. The minimum distance(J) is given by ,

$$J = \text{argmin}(D_m)$$

Notation

Parameter	Definition
μ_{mr}	Mean value of trained image for red channel
μ_{mg}	Mean value of trained image for green channel
μ_{mb}	Mean value of trained image for blue channel
μ_{xr}	Mean value of test image for red channel
μ_{xg}	Mean value of test image for green channel
μ_{xb}	Mean value of test image for blue channel
σ_{mr}	Standard Deviation value of trained image for red channel
σ_{mg}	Standard Deviation value of trained image for green channel
σ_{mb}	Standard Deviation value of trained image for blue channel
σ_{xr}	Standard Deviation value of test image for red channel
σ_{xg}	Standard Deviation value of test image for green channel
σ_{xb}	Standard Deviation value of test image for blue channel
I_{trainr}	Values of mean and standard deviation (μ_{mr}, σ_{mr}) of a trained image for red channel
I_{traing}	Values of mean and standard deviation (μ_{mg}, σ_{mg}) of a trained image for green channel
I_{trainb}	Values of mean and standard deviation (μ_{mb}, σ_{mb}) of a trained image for blue channel
I_{testr}	Values of mean and standard deviation (μ_{xr}, σ_{xr}) of a test image for red channel

I_{testg} Values of mean and standard deviation (μ_{xg}, σ_{xg}) of a test image for green channel

I_{testb} Values of mean and standard deviation (μ_{xb}, σ_{xb}) of a test image for blue channel

D_m Distance (D) between a 'mth' trained image and a test image

$[D]$ 288x1 Matrix with the distances between a test image and 288 images

4.2.3. Results for Color Images

The plots of mean and standard deviation for three different channel under different climatic conditions for three different color channels and the results are observed.

4.2.3.1. Histogram Plots

a) Mean

The mean of the images under three different conditions are plotted below. When an image is captured from a mobile camera, the image's brightness is compensated and also the it is histogram equalized as it is the default feature of the camera. It also masks the original mean values of the image.

Condition 1 – Rainy

In figure 38 , the mean values of red channel of the color images are plotted for rainy climatic condition. It can be observed that the mean values are distributed, and maximum number of values lie in between 118 and 122.

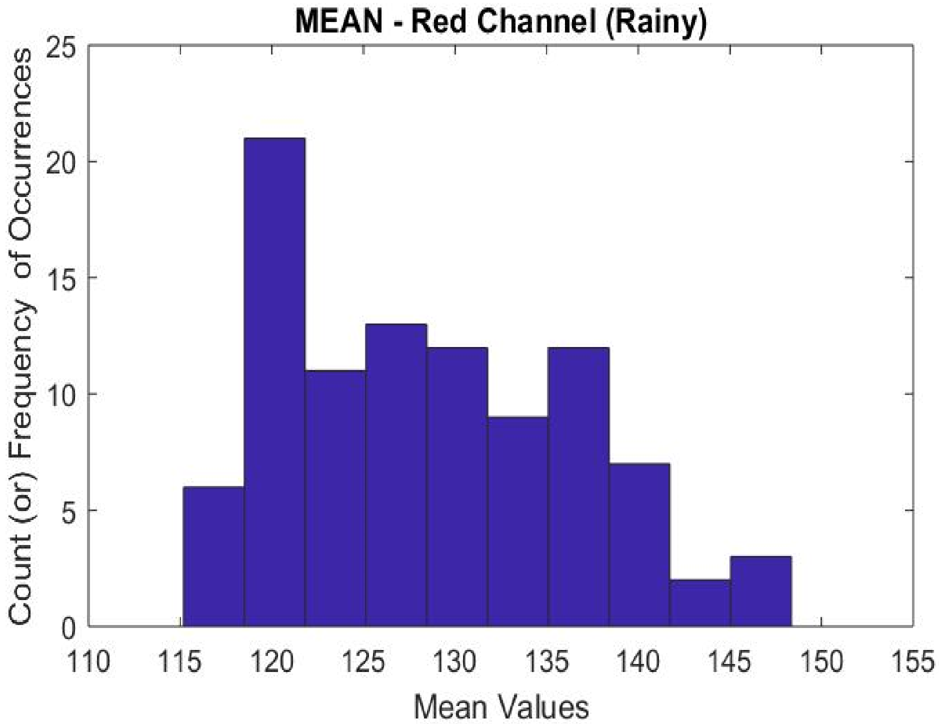


Figure 38: Histogram plot of Mean values(Red Channel) – Rainy

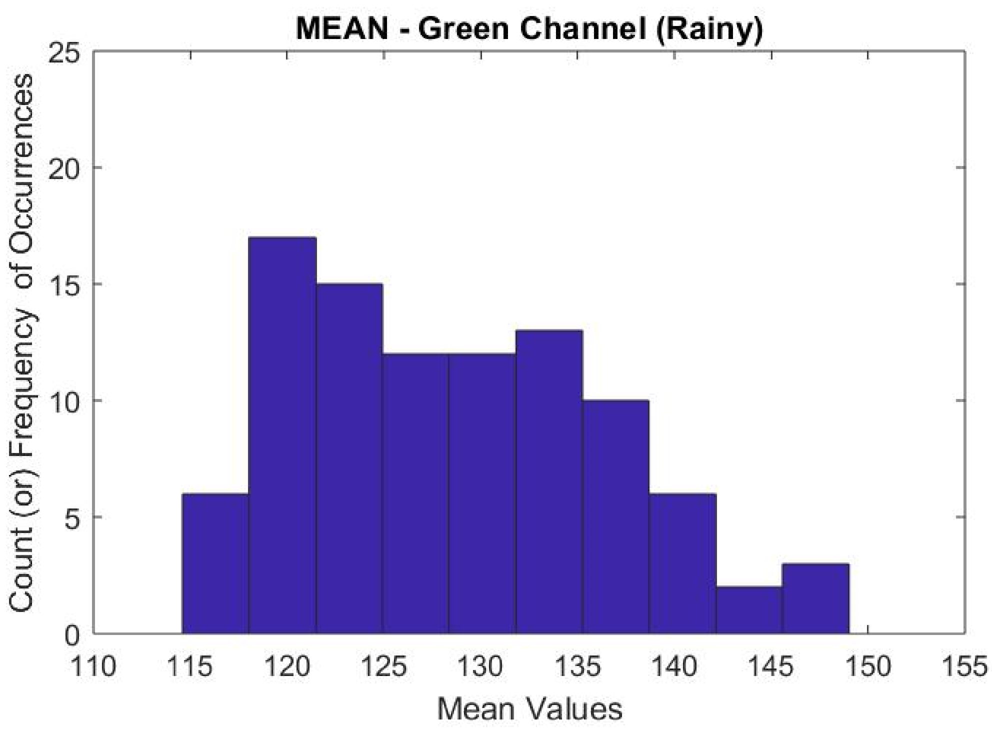


Figure 39: Histogram plot of Mean values(Green Channel) – Rainy

In figure 39, the mean values of green channel of the color images are plotted for rainy climatic condition. It can be observed that the mean values are distributed, and maximum number of values lie in between 118 and 122.

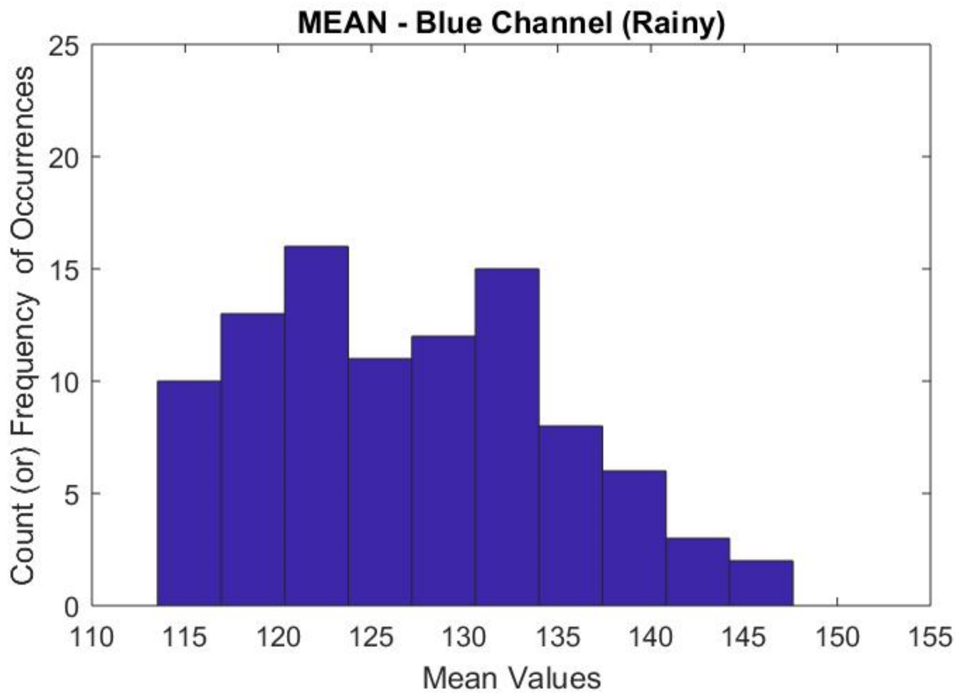


Figure 40: Histogram plot of Mean values(Blue Channel) – Rainy

In figure 40, the mean values of blue channel of the color images are plotted for rainy climatic condition. It can be observed that the mean values are distributed, and maximum number of values lie in between 120, 125 and 130,135.

Condition 2 – Cloudy

The occurrence of mean values of the color images in red channel are plotted for cloudy climatic condition in figure 41. It can be observed that the mean values are distributed between 122 and 150. The maximum number of values lie in between 130 and 133.

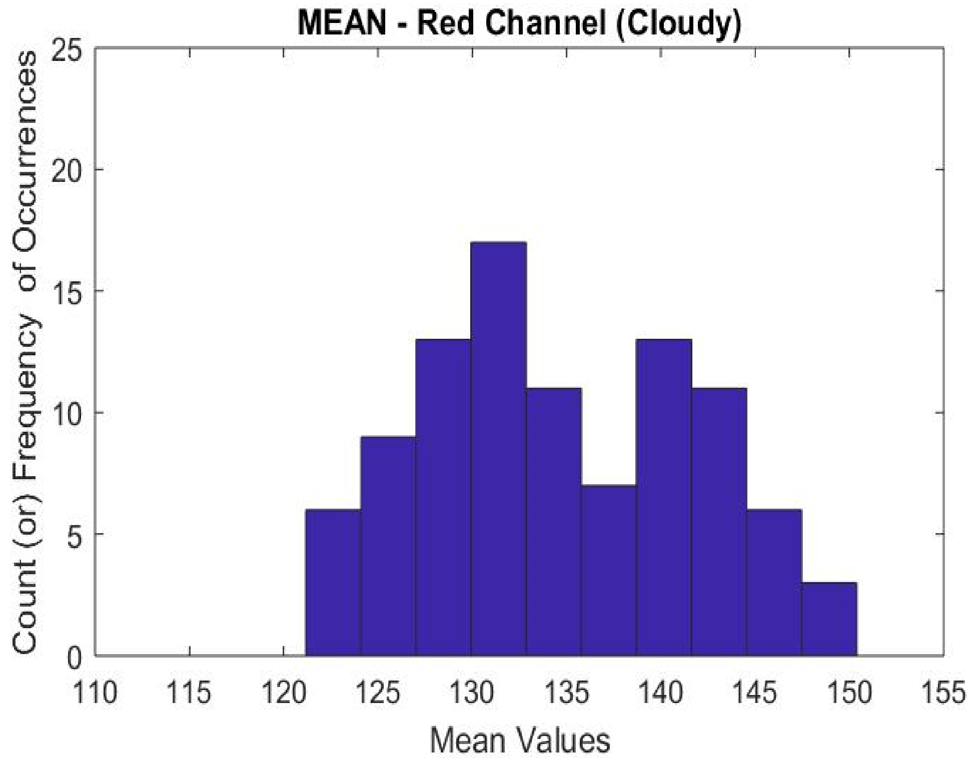


Figure 41: Histogram plot of Mean values(Red channel)- Cloudy

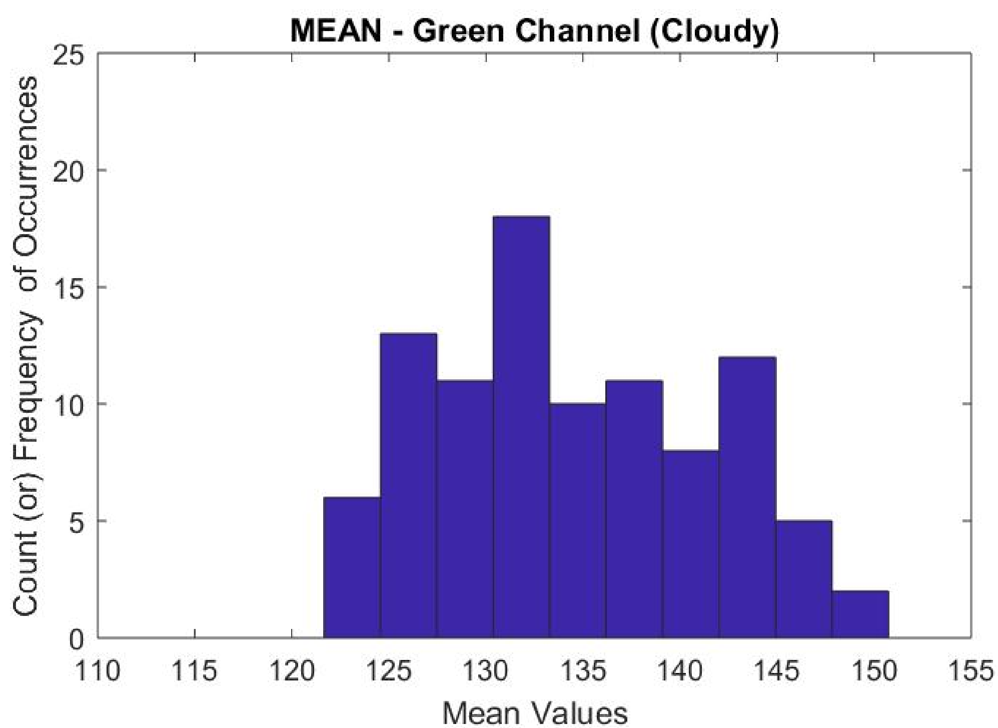


Figure 42: Histogram plot of Mean values(Green channel)- Cloudy

From figure 42, the occurrence of mean values of the color images in the green channel are plotted for cloudy climatic condition. It can be observed that the mean values are distributed between 122 and 150. The maximum number of values lie in between 130 and 133.

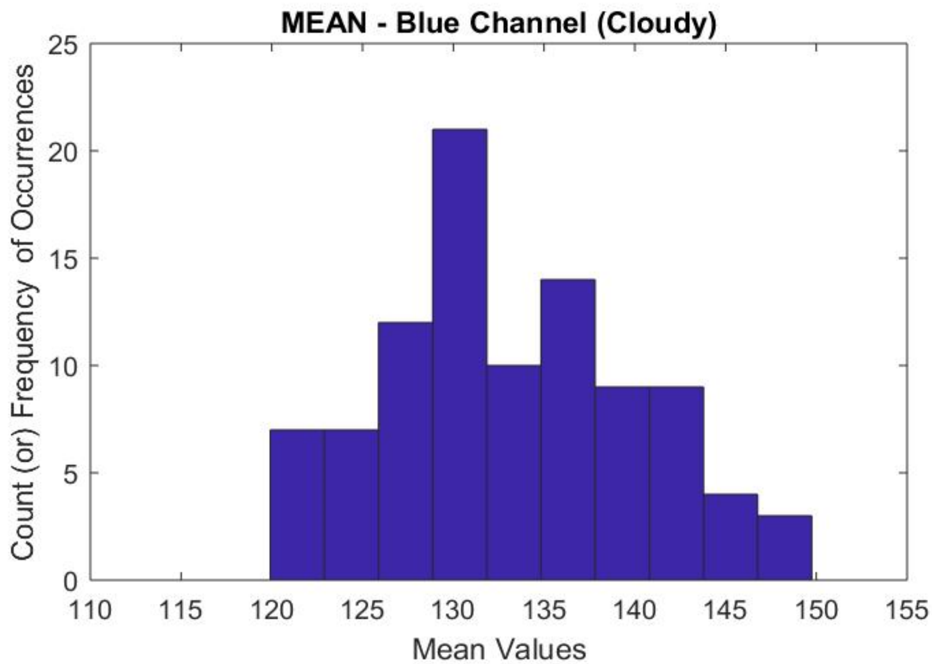


Figure 43: Histogram plot of Mean values(Blue channel)- Cloudy

The occurrence of mean values of the color images in red channel are plotted for cloudy climatic condition in figure 43. It can be observed that the mean values are distributed between 120 and 150. The maximum number of values lie in between 128 and 133.

Condition 3 – Sunny

In figure 44, the of mean values are plotted with the frequency of occurrences for red channel under sunny climatic condition. It can be observed that the mean values are distributed between 110 and 150, and maximum number of values lie in between 130 and 135.

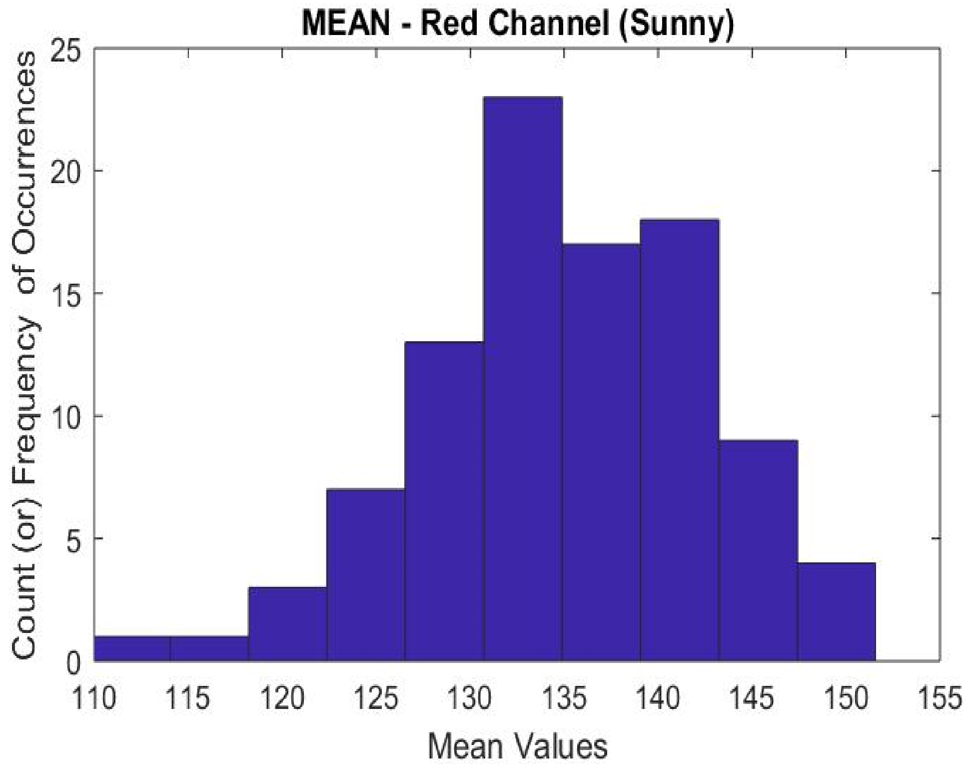


Figure 44: Histogram plot of Mean values(red channel) - Sunny

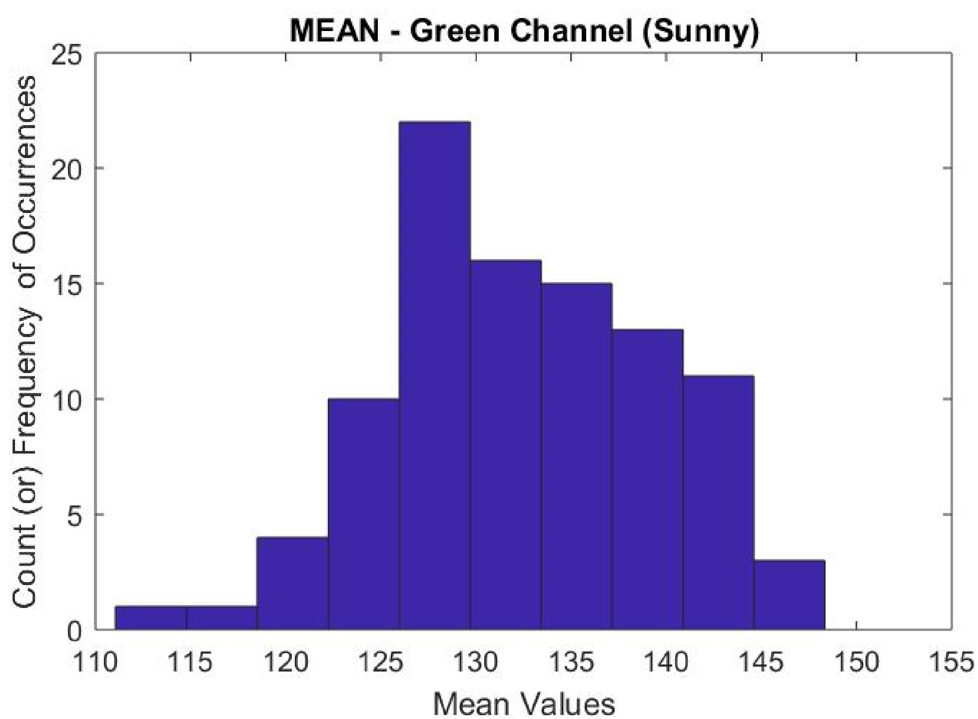


Figure 45: Histogram plot of Mean values(green channel) - Sunny

From figure 45, the of mean values are plotted with the frequency of occurrences for green channel under sunny climatic condition. It can be observed that the mean values are distributed between 111 and 148, and maximum number of values lie in between 125 and 130.

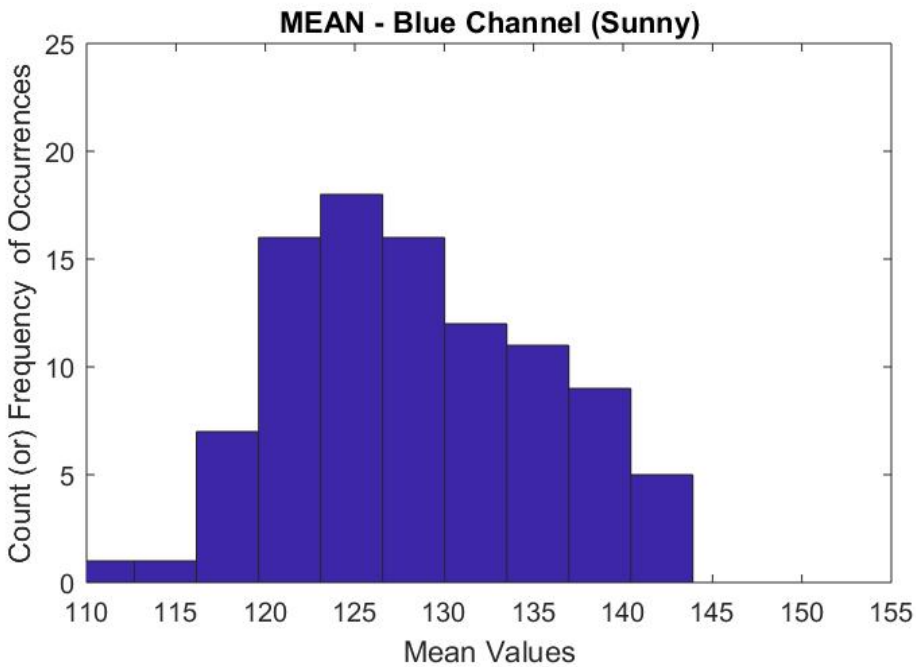


Figure 46: Histogram plot of Mean values(blue channel) - Sunny

In figure 46, the of mean values are plotted with the frequency of occurrences for red channel under sunny climatic condition. It can be observed that the mean values are distributed between 110 and 144, and maximum number of values are widespread between 120 and 130.

From all the above histogram plots of mean values for various climatic conditions it can be observed that the mean values are distributed in between the range 110 and 150. Though the mean values are distributed, the frequency of occurrence of mean values is different for different channels for different climatic conditions .

The contribution intensity of the individual pixel values of an image is given by mean. Each and every pixel in a color image has 3 channels :red, green and blue. The high mean value indicates that the intensity of a pixel value was high. From the above histogram plots of mean , the effect of histogram equalization and the compensation of brightness can be observed since the mean values are not widespread.

b) Standard Deviation

Condition 1 – Rainy

In figure 47, the frequency of occurrences of standard deviation values of color images in red channel are plotted for rainy climatic condition. It can be observed that the Standard deviation values are distributed between 1 and 17 but maximum number of values lie in between 2 and 3.

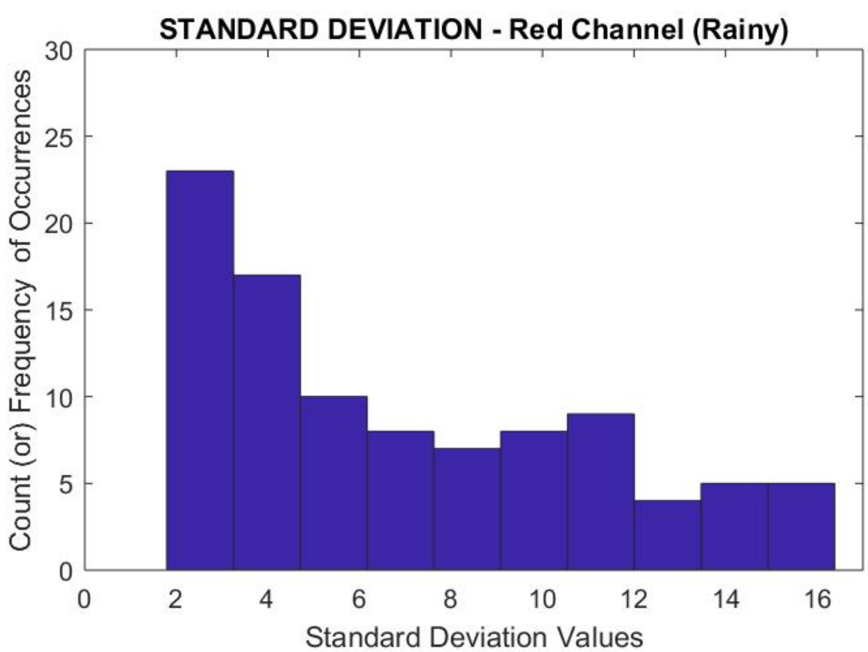


Figure 47: Histogram plot of Standard Deviation values(red channel) – Rainy

From figure 48, the of standard deviation values are plotted with the frequency of occurrences for green channel under rainy climatic condition. It can be observed that the standard deviation values are distributed between 1 and 16, and maximum number of values lie in between 2 and 3.

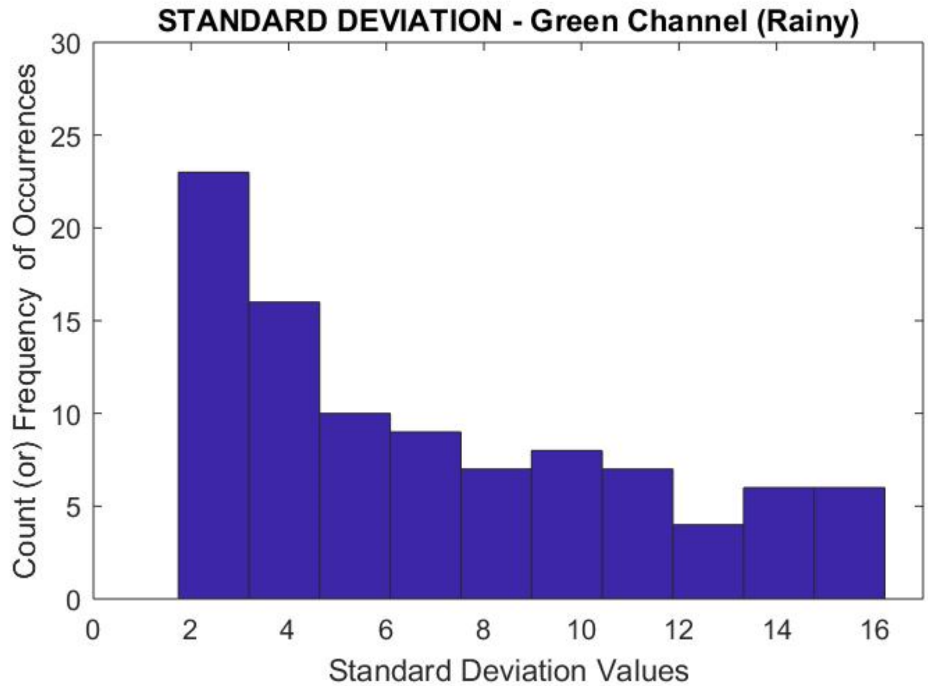


Figure 48: Histogram plot of Standard Deviation values(green channel) – Rainy

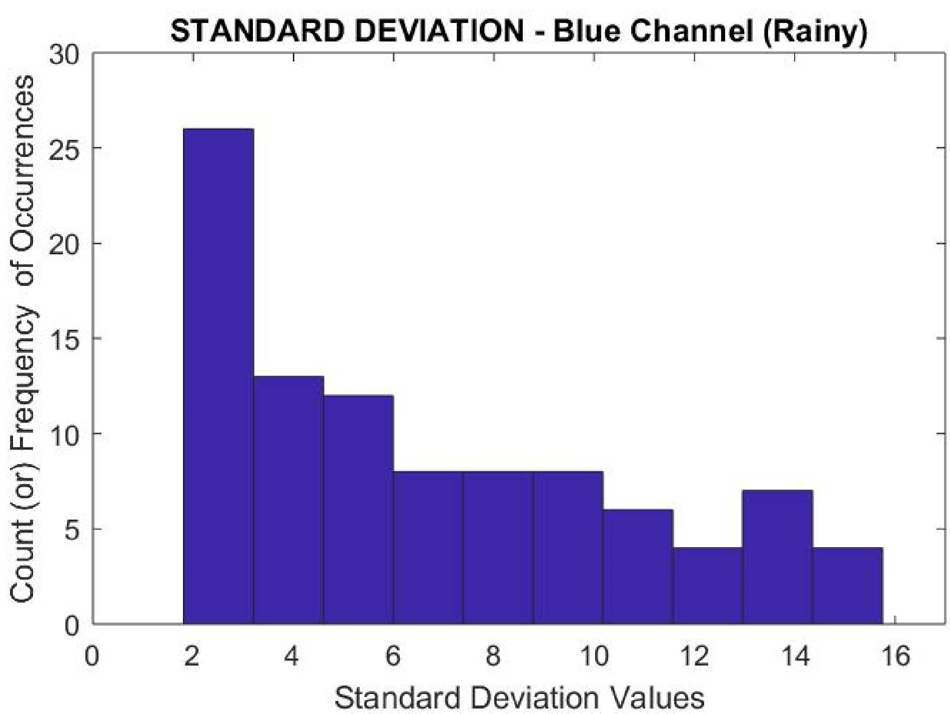


Figure 49: Histogram plot of Standard Deviation values(blue channel) – Rainy

In figure 49, the frequency of occurrences of standard deviation values of color images in blue channel are plotted for rainy climatic condition. It can be observed that the Standard deviation values are distributed between 1 and 16 but maximum number of values lie in between 2 and 3.

Condition 2 – Cloudy

The frequencies of standard deviation values for red channel are plotted under cloudy climatic condition in figure 50. It can be observed that the standard deviation values are distributed between 1 and 14. The maximum number of values lie in the interval of 1 and 4.

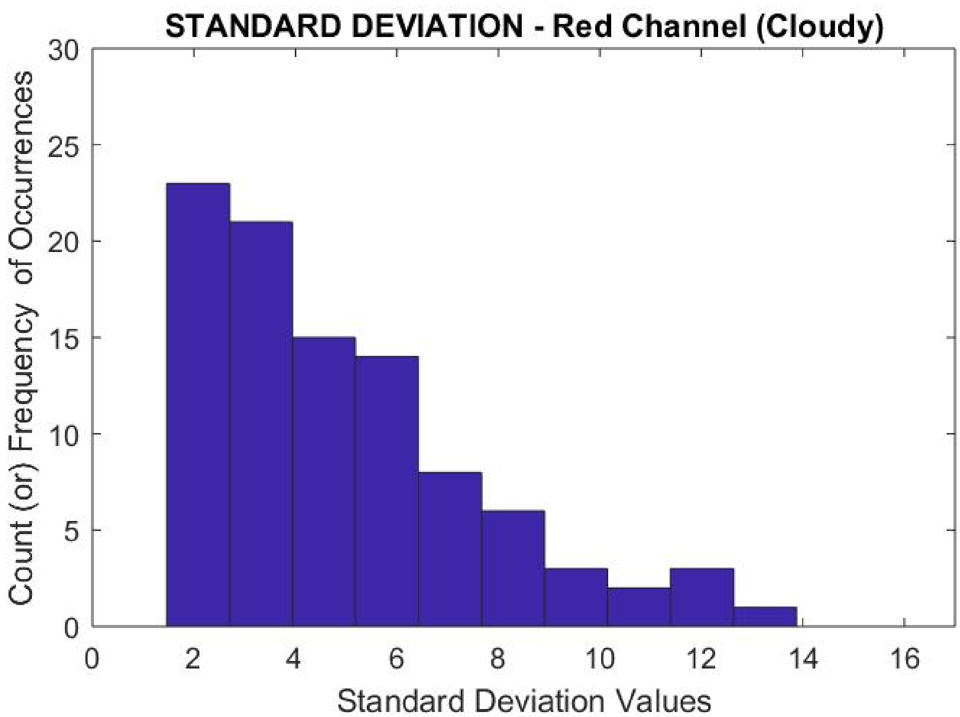


Figure 50: Histogram plot of Standard Deviation values(red channel) – Cloudy

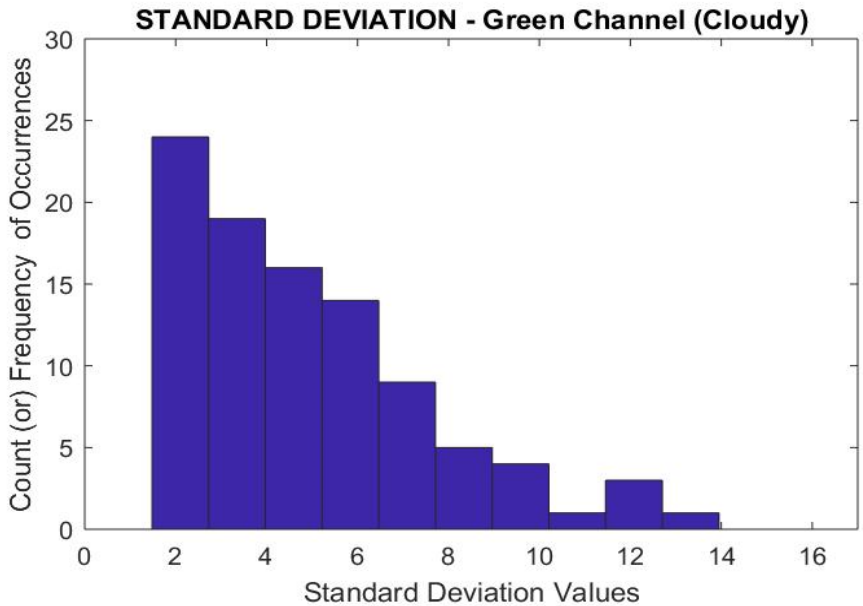


Figure 51: Histogram plot of Standard Deviation values(green channel) – Cloudy

In figure 51, the of standard deviation values are plotted with the frequency of occurrences for green channel under cloudy climatic condition. It can be observed that the standard deviation values are distributed between 1 and 14, and maximum number of values lie in between 1 and 3.

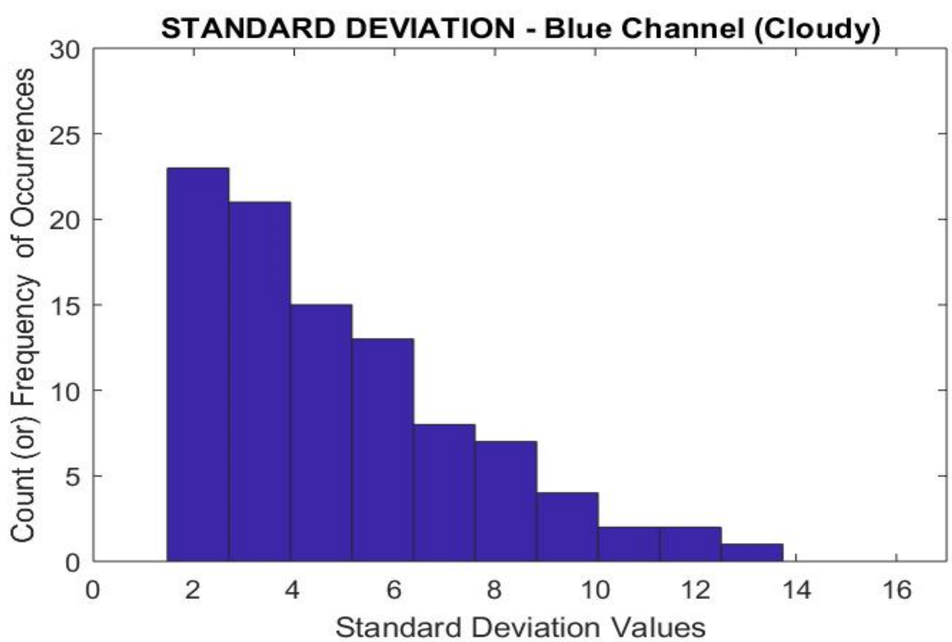


Figure 52: Histogram plot of Standard Deviation values(blue channel) – Cloudy

The frequencies of standard deviation values for blue channel are plotted under cloudy climatic condition in figure 52. It can be observed that the standard deviation values are distributed between 1 and 14. The maximum number of values lie in the interval of 1 and 4.

Condition 3 – Sunny

In figure 53, the frequencies of standard deviation values for red channel are plotted under sunny climatic condition. It can be observed that the standard deviation values are distributed between 1 and 14, but maximum number of values lie in between 3 and 4.

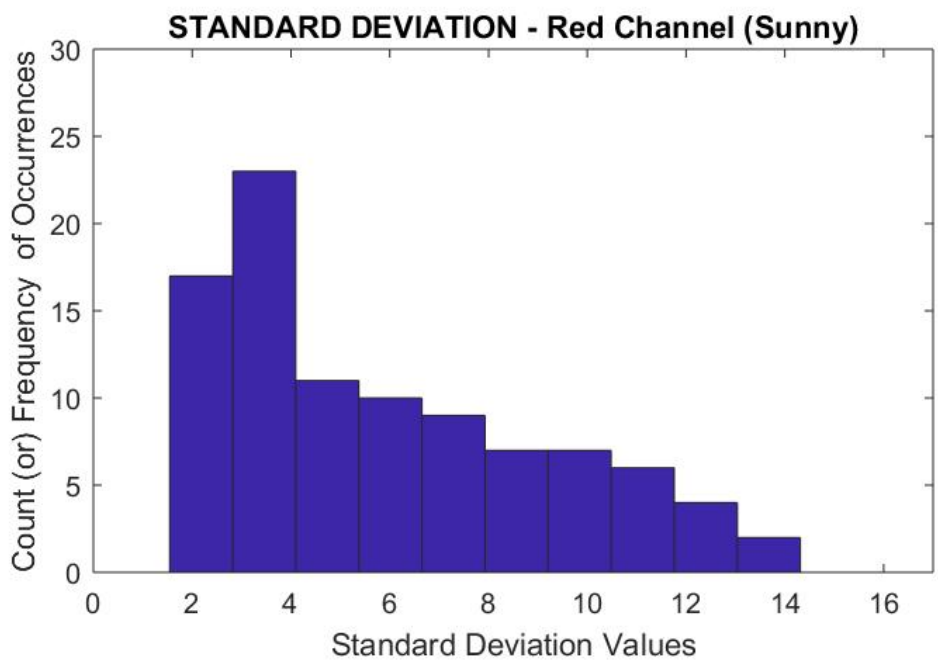


Figure 53: Histogram plot of Standard Deviation values(red channel) - Sunny

From figure 54, the of standard deviation values are plotted with the frequency of occurrences for green channel under sunny climatic condition. It can be observed that the standard deviation values are distributed between 1 and 15, and maximum number of values lie in between 3 and 4.

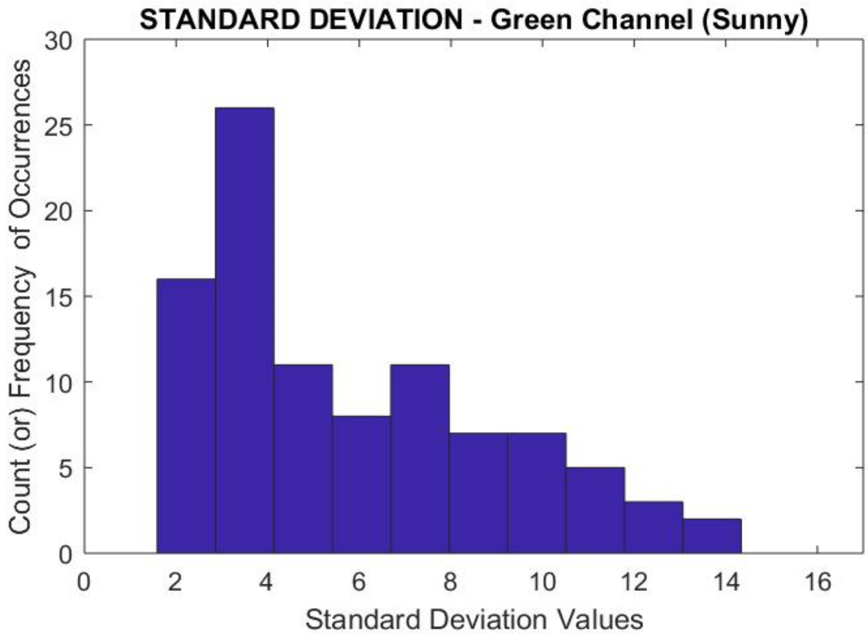


Figure 54: Histogram plot of Standard Deviation values(green channel) - Sunny

The frequencies of standard deviation values for blue channel are plotted under sunny climatic condition in figure 55. It can be observed that the standard deviation values are distributed between 1 and 14. The maximum number of values lie in the interval of 1 and 4.

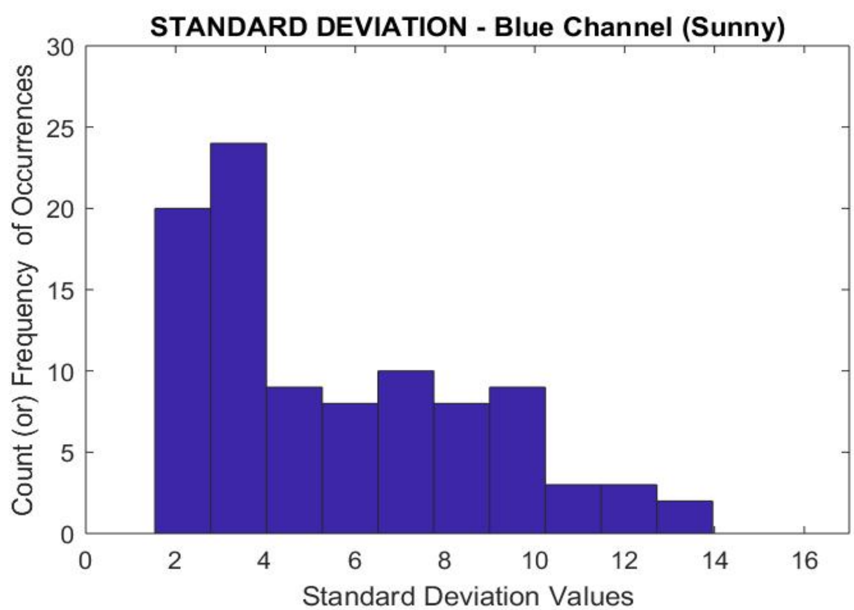


Figure 55: Histogram plot of Standard Deviation values(blue channel) - Sunny

The amount of variation of the pixel values is given by standard deviation. From all the above histogram plots of standard deviation values for various climatic conditions it can be observed that the standard deviation values are distributed in between the range 1 and 16. Though the standard deviation values are distributed, the frequency of occurrence of standard deviation values is almost same that is all the values lie in between 2 and 5 for different climatic conditions for different channels. The standard deviation values lie in almost similar region because a standard deviation value depends upon the variation of a pixel intensity in an image. In an image if all the pixel values tend to be closer, the standard deviation value is less.

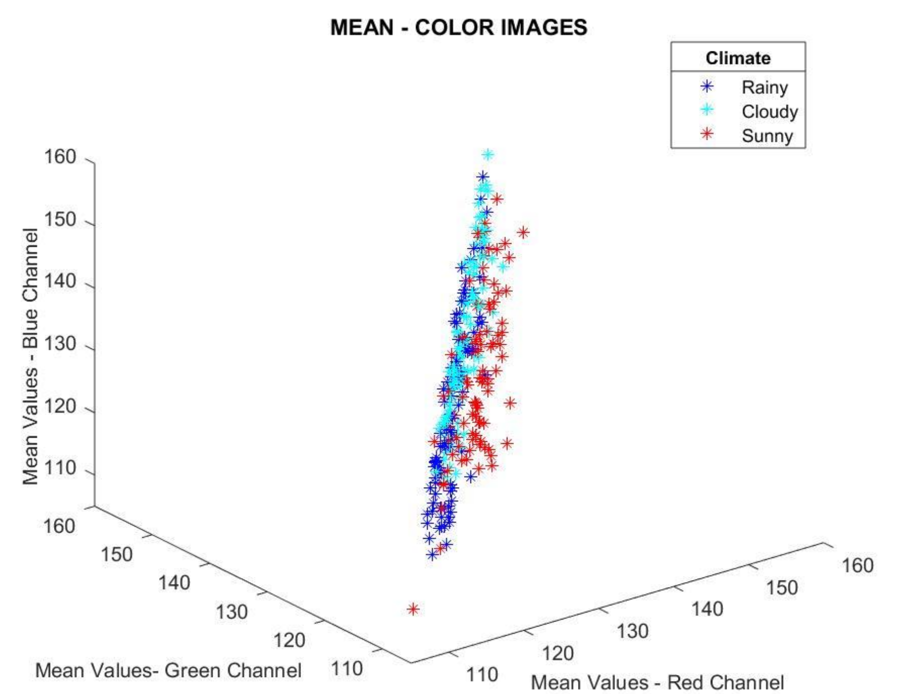


Figure 56: 3D Plot of mean values of different color channels under different climatic conditions

The values of mean for all three climatic conditions are plotted in the 3D plot in figure 56. From the plot it can be observed that the values of mean for various climatic conditions overlap on each other. Different climatic conditions are represented in different colors: blue color for climatic condition rainy, cyan for cloudy and red for sunny climatic condition. All the mean values lie in the range 110 and155. These values did not form any separate clusters to differentiate the climatic conditions. If there were different clusters formed then centroid of each cluster would have been helpful in classifying the images.

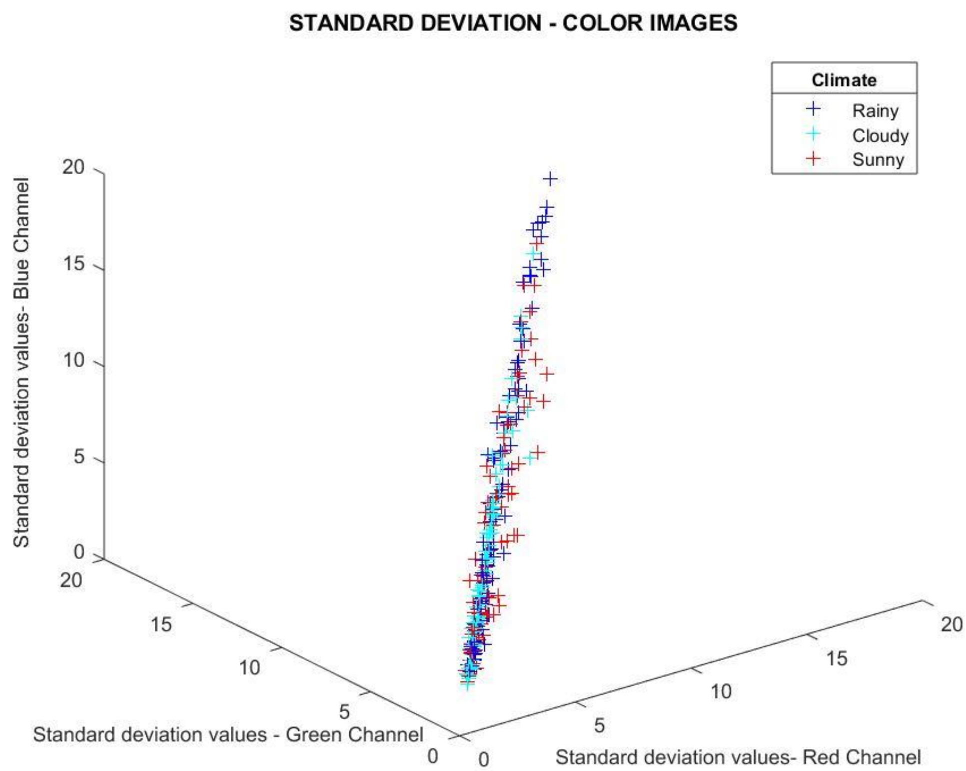


Figure 57: 3D Plot of standard deviation values of different color channels under different climatic conditions

In figure 57, the values of standard deviation values for all three climatic conditions are plotted in the 3D plot. From the plot it can be observed that the values of standard deviation for various climatic conditions overlap on each other. Different climatic conditions are represented in different colors: blue color for climatic condition rainy, cyan for cloudy and red for sunny climatic condition. All the standard deviation values are not separated, and all the values lie between 1 and 16.

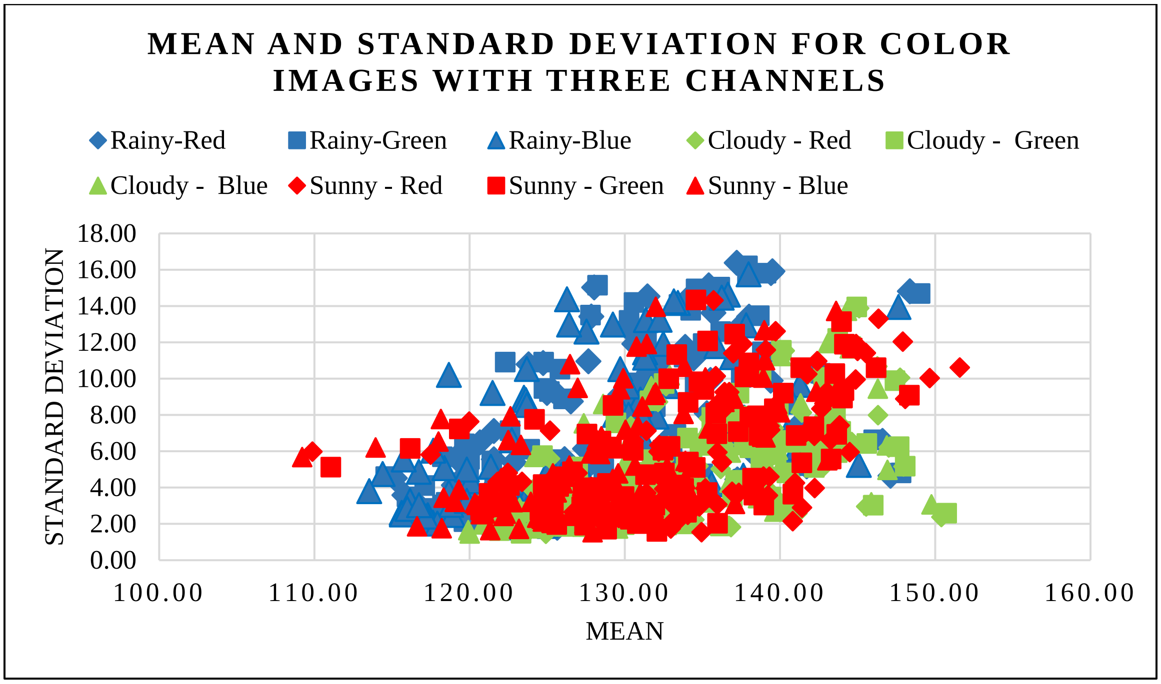


Figure 58: Plot of mean and standard deviation values of different color channels under different climatic conditions

From figure 58 it can be observed that the mean and standard deviation values did not form any separate clusters to differentiate the climatic conditions. All the values are overlapping. The classification of the images would have been easier if there were different cluster formed.

4.2.3.2. Testing Process

The input for testing algorithm for image classification is selected from the other random images but not from the trained images. The figure 59 shows the input color test image. The test image has no water.

Figure 59: Input color image for testing

From the test image features are extracted and are stored as test features. “Ftest” in the figure 60 represents the extracted mean and standard deviation values for three channels respectively. These test image values and the trained image values are the inputs for equation 2 in section 4.2.2 to find the distance D. Once the distance is determined for all the trained images with test image, then the minimum distance from all the distance in the matrix D_m . The output is displayed in figure 60. There are various examples discussed in the section 4.1.1.

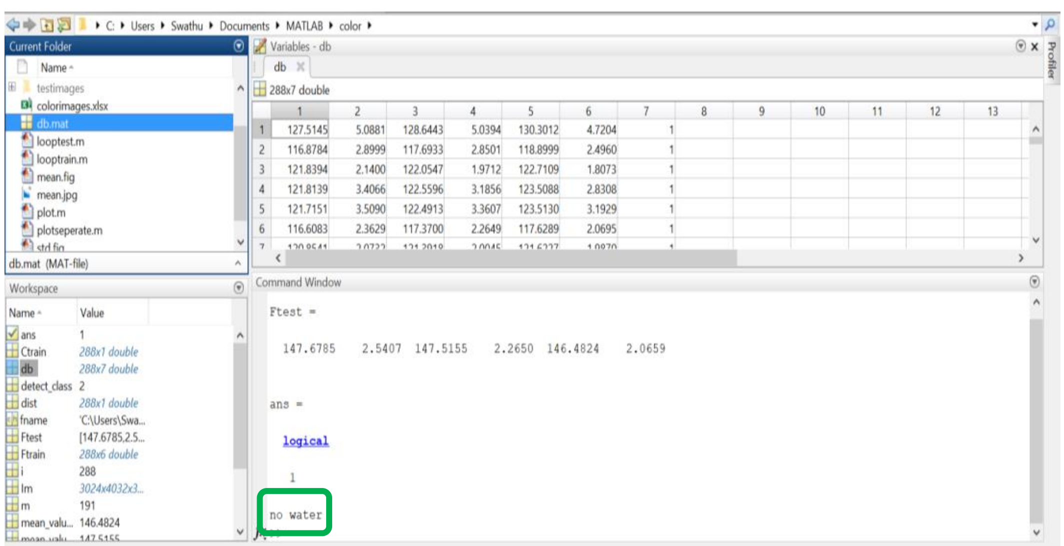


Figure 60: Output of image classification system for color images

The test image which was fed to the image classifier had no water, the image classifier classified the image correctly that it has no water. Since there is water present in only in the rainy climatic condition and not in other conditions: sunny and cloudy, the algorithm give output as water if class 1 is detected and no water if either class-2 or class-3 is detected. The output image screenshot, Figure 60 has mean and standard deviation values of the test image and the output is highlighted. There are various examples discussed in the section 4.3.1.

4.3. Results and Limitations

4.3.1. Comparison of Results

The accuracy of classification algorithms is to be tested. Accuracy is given by,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Formula 1

In the formula,

TP(True Positives) = Correctly classifying an image with water as an image with water.

TN(True Negatives) = Correctly classifying an image with no water as an image with no water.

FP(False Positives) = Incorrectly classifying an image with no water as an image with water.

FN(True Negatives) = Incorrectly classifying an image with water as an image with no water.

Image Classification algorithm with gray scale images and image classification algorithm with color images

Table 1: Comparison of image classification algorithm for gray scale images and color images

Images	**Image classification (Grayscale Images)**	**Image classification (Color Images)**
Image 1 (no water)	Wrong(FP)	Wrong(FP)
Image 2 (no water)	Correct(TN)	Correct(TN)
Image 3 (no water)	Correct(TN)	Correct(TN)
Image 4 (no water)	Correct(TN)	Correct(TN)
Image 5 (no water)	Correct(TN)	Correct(TN)
Image 6 (no water)	Correct(TN)	Correct(TN)
Image 7 (no water)	Correct(TN)	Correct(TN)
Image 8 (no water)	Correct(TN)	Correct(TN)
Image 9 (no water)	Correct(TN)	Correct(TN)
Image 10(no water)	Correct(TN)	Correct(TN)
Image 11 (water)	Correct(TN)	Correct(TN)
Image 12 (water)	Wrong(FN)	Wrong(FN)
Image 13 (water)	Correct(TP)	Correct(TP)
Image 14 (water)	Wrong(FN)	Correct(TP)
Image 15 (water)	Wrong(FN)	Correct(TP)
Image 16 (water)	Correct(TP)	Correct(TP)
Image 17 (water)	Correct(TP)	Wrong(FN)
Image 18 (water)	Correct(TP)	Correct(TP)
Image 19 (water)	Correct(TP)	Correct(TP)
Image 20 (water)	Correct(TP)	Correct(TP)

i. Accuracy of Image Classification Algorithm(Gray scale images)

Table 2: Accuracy of Image classification Algorithm(Gray scale)

	No Water	**Water**
No Water	9 (TN)	1 (FP)
Water	3 (FN)	7 (TP)

Accuracy of Image classification Algorithm (Gray Scale) = 80%

ii. Accuracy of Image Classification Algorithm(Color images)

Table 3: Accuracy of Image classification Algorithm(color images)

	No Water	**Water**
No Water	9 (TN)	1 (FP)
Water	2 (FN)	8 (TP)

Accuracy of Image classification Algorithm(Color images) = 85%

The above tables display the total accuracy of the image classification algorithm with gray scale images and color images. Some cases from table 1 are discussed below.

Examples

Case 1:

The image classification algorithm trained with gray scale images and color images has classified their respective form of test image correctly. This test image has sand in it and there is no water. The image can be observed in table 4.

Table 4: Correct Image classification with grayscale and Correct Image classification with color image

Algorithm	**Image classification with Grayscale images (Correct)** **Image classification with Color images (Correct)**
Image (no water)	

Case 2:

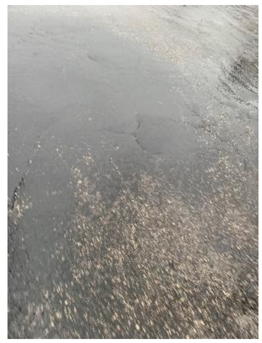
Table 5: Correct Image classification with grayscale and wrong Image classification with color image

Algorithm	**Image classification with Grayscale images (Correct)** **Image classification with Color images (Wrong)**
Image (water)	

The image classification algorithm trained with gray scale images has classified the test image correctly, but the algorithm trained with color images has not classified the test image correctly. The above test image has a white line and water. The test image looks glossier due to the presence of water. The algorithm trained with color images might have not extracted these features. So, the image classification algorithm trained with color scale images detected this image inaccurately.

Case 3:

Table 6: Wrong Image classification with grayscale and Correct Image classification with color image

Algorithm	**Image classification with Grayscale images (Wrong)** **Image classification with Color images (Correct)**
Image (water)	

The image classification algorithm trained with gray scale images has classified the test image incorrectly whereas the algorithm trained with color images has classified the test image correctly. The above image has water and it appears to be glossier. So, part of the image appears to be dark and other to be light and also the road surface color is uneven. The algorithm trained with gray images might have not extracted these features. So, the image classification algorithm trained with color scale images detected this image accurately.

Case 4:

The image classification algorithm trained with gray scale images and color images has classified their respective form of test image incorrectly which can be observed in table 7. In the above test image, there is a shadow of an object on the road. Some part of the road appears to be darker because of shadow in the image. The features in this image might be similar to the images which has water. So, the algorithm trained with grayscale images and color images classified the image incorrectly.

Table 7: Wrong Image classification with grayscale and Wrong Image classification with color image

Algorithm	**Image classification with Grayscale images (Wrong)** **Image classification with Color images (Wrong)**
Image (no water)	

The accuracy of image classification algorithm color images is slightly greater than the accuracy with gray scale images. One of the main reasons for increase in accuracy is that when the color images are considered there is no preprocessing done: converting into grayscale. The images are considered as the original images.

4.3.2. Limitations

The presented image classification algorithm has a defined set of images that are trained. Since the images are taken in a particular way and system is only trained with those images, the algorithm might not give accurate results when other images from a different set are used for testing. For example, all the images were captured using the mobile phone. Consider a random image from google maps in pedestrian mode. If this google image is given as a test image the algorithm might not give correct result, because the network system which was trained had only particular type of images and not random images. If the system is trained with random images, then the system might give accurate results for random test images.

5. MACHINE LEARNING

5.1 Introduction

A first wave of interest in neural networks has become prominent after the proposal of simplified neurons by McCulloch and Pitts in 1943 [59]. The biological neurons were used to represent these neurons and as the components to perform tasks for various computational models in a circuit. But this interest did not last long when the concept of perceptron and its drawbacks came into light (1969). But in later eighties when some theoretical results were obtained the interest re-emerged [59].

A neural network is a layered computational model which mirrors the structure of neurons in human brain. Neural networks can study and analyze the data, so pattern recognition, classification of data and forecasting the events is possible by training the neural network. Like human brain, neural network can be trained to recognize image, pattern or speech by breaking the input into different layers. Depending upon the number of layers and the data available, training a neural network can be classified into two types: Deep learning and Machine learning.

Deep learning is complex, and it is a subtype of Machine learning. For deep leaning high performance GPU and large amount of labeled data is required. In deep learning there is no process of manual extraction of features. Images are directly fed into the deep learning algorithm which has three or more layers. Machine learning is simple, and it does not require large amounts of data. In Machine learning, few relevant features of an image such as edges or corners to train the model. The model then references those features to analyze and classify the images, patterns or objects.

5.2 Algorithm

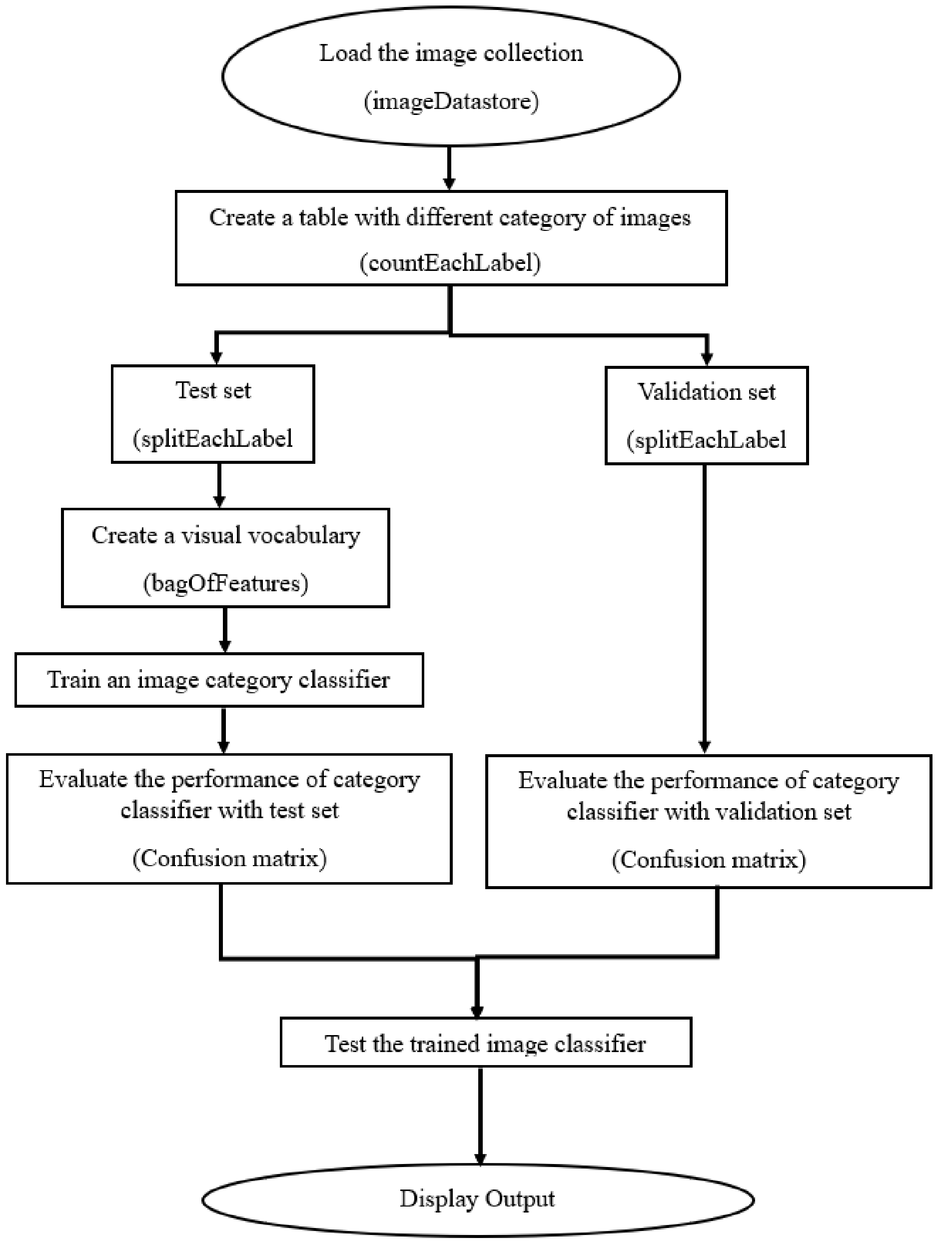


Figure 61: Algorithm for machine learning

A set of images are given as input to the network. This set of images have images from different categories. A table with different labels or categories is created and also the number of images present in each label is displayed.

The machine learning toolbox in MATLAB was used. All the images under different labels are divided into two sets: training set and validation set. The percentage of images which are to be distributed into training set and validation set can be given manually.

Visual vocabulary is created from the images that are present in the training set by using different functions. In the next step, the features from the different category of images are collected in a category classifier. Clusters are formed in different regions with respect to the extracted features from the different categories.

Now the performance of the category classifier and the training set are evaluated. The default output is a confusion matrix. From the confusion matrix the accuracy can be known. Similarly, the same process is done with category classifier and the validation set. A confusion matrix is generated from which the accuracy can be known.

The trained network is ready for testing purpose. An image is given as input to the trained network. The features of the test image are compared with the features of the trained images. Once the closest features are matched in a region, the output is displayed with the category name of the image.

5.3 Functions

a) imageDatastore

ImageDatastore object is used to store the collection images with different categories. Memory is allocated to each image but sometimes this memory may not be enough to store entire collection of images. An ImageDatastore object can be created by either using the imageDatastore function or the datastore function. This function refers to the file location of the collection of images. Since imageDatastore operates on image file locations, therefore it does not load all the images into memory and is safe to use for large image collections [60].

b) countEachLabel

The countEachLabel function helps to find the number of images under each category and the values can be returned in the form of a table(tbl) [61].

c) montage

The process of selecting and piecing together of the separate images is called montage. The montage function in MATLAB displays all the frames of a multi frame image array. Images can be selected from different categories and they can be different sizes. The number of images to be displayed in a rectangular montage can be set manually according to the application .

d) splitEachLabel

The splitImageLabel splits the labels which are the categories that are present in ImageDatastore by different percentages or proportions. The percentage values can be given as per the requirement. Let 'alpha' and 'beta' be to different sets, assume 55 percent of images from cat, dog and monkey categories are to be added to alpha set and remaining 45 percent images are to be added to beta set. This operation can be done using splitEachLabel function [62].

e) Confusion matrix and evaluate

The evaluate function helps in evaluating the performance of a classifier with a training set and a validation set. By default, evaluate function returns the confusion matrix. The accuracy of the classifier can be obtained by the combination of confusion matrix and the evaluate function [63].

f) bagOfFeatures

The bagOfFeatures function is generally used to create a visual vocabulary. In the world of natural processing computer vision is adapted by a technique called bag of words. All the images do not contain discrete words, so to form the vocabulary – SURF (Speeded Up Robust Features) is used to recognize various features from different categories [64].

The SURF is used for classification, three-dimensional (3D) reconstruction, image registration or object recognition. SURF is a patented local feature descriptor and detector in the computer vision. In image processing it is used to extract the key points from different regions of an image. It uses wavelet responses in both horizontal and vertical directions by applying adequate Gaussian weights. SURF uses the wavelet responses for feature description. Generally, the strongest features from each category are extracted [64].

The single call of bagOfFeatures function extracts: all SURF features from all images in all the categories and constructs the visual vocabulary by decreasing the number of features by K-means clustering. Quantization of features is the technique used from K-means clustering. Clustering in image classification is grouping data points of same category of data in different regions. Once the grouping is done then the clusters of similar features are formed. Clustering can be done in any number of iterations which results in creating Bag-Of-Features [64].

5.4 Results

5.4.1 Results of machine learning algorithm

a) Load Image Dataset

The machine learning algorithm is trained by color images as captured. To load the images into a dataset first unzip the images if the images are in a zip folder. Then load the image collection by giving the file location. The images that are loaded are color images. Create a table with number of images under each category. A total of 200 images were trained of which 100 were with water and 100 without water.

b) Train and Validation Image Sets

Once the image dataset is loaded, depending upon the percentage, the image-sets are split into training set and validation set. In this application training set has 70% of images from different labels and remaining 30% of images under validation set from different labels. A function is used to pick random images from each set. This step returns two imageDatestore objects that are ready for training and validation tasks.

c) Image classifier

Visual vocabulary function is used for the training set. And the features from different sets of images are collected. Now, the quantization process takes place. The number of features and the number of clusters formed can be seen. there is an iteration process that goes on many number of times till the key points are extracted which helps in image classification. A Bag-Of-Features are created.

Table 8: Creating Bag-Of-Features for images

```
Creating Bag-Of-Features.
-------------------------
* Image category 1: nowater
* Image category 2: water
* Selecting feature point locations using the Grid method.
* Extracting SURF features from the selected feature point
  locations.
** The GridStep is [8 8] and the BlockWidth is [32 64 96 128].
* Extracting features from  140 images...done. Extracted 18289152
features.
* Keeping 80 percent of the strongest features from each
  category.
* Using K-Means clustering to create a 500word visual vocabulary.
* Number of
features       : 14631322
* Number of
clusters (K)   : 500
* Initializing
cluster centers...100.00%.
             completed 28/100 iterations (~168.00        converged.
* Clustering.seconds/iteration)...                       in
28
iterations.
* Finished creating Bag-Of-Features
```

d) *Visual word occurrences*

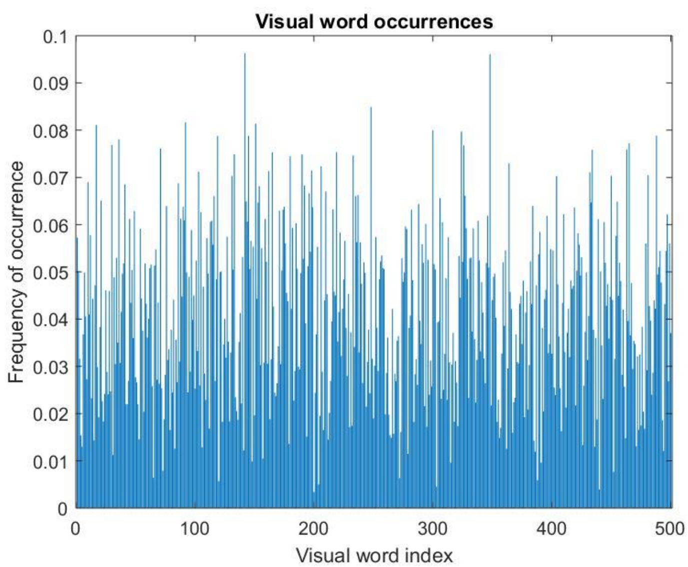


Figure 62: Visual word occurrences of images

e) Category Classifier

The training images that are encoded from each label or category are fed into the category classifier training process invoked by the train image category classifier function. This function relies on Machine learning toolbox. The output is as follows.

Table 9: Training of an image classifier

```
Training an image category classifier for 2 categories.
--------------------------------------------------------
* Category 1: nowater
* Category 2: water
* Encoding features for 140 images...done.

* Finished training the category classifier.
```

f) Evaluate Classifier Performance

The category classifier performance is evaluated with the training set and also with the validation set. The default output is the confusion matrix. It gives the average accuracy of category classifier with respect to training set and validation set.

Category classifier and Training set

Table 10: Evaluation of category classifier and training set

```
Evaluating image category classifier for 2 categories.
-------------------------------------------------------
* Category 1: nowater
* Category 2: water
* Evaluating 24 images...done.
* Finished evaluating all the test sets.
* The confusion matrix for this test set is:

               PREDICTED
KNOWN     | nowater  water
---------------------------
nowater   | 0.83     0.17
water     | 0.35     0.75

* Average Accuracy is 0.79.
```

Category classifier and Validation set

Table 11: Evaluation of category classifier and validation set

```
Evaluating image category classifier for 2 categories.
-------------------------------------------------------
* Category 1: nowater
* Category 2: water
* Evaluating 60 images...done.
* Finished evaluating all the test sets.
* The confusion matrix for this test set is:



               PREDICTED
         |
KNOWN    nowater  water
-------------------------------
nowater  | 1.00    0.00
water    | 0.38    0.63

* Average Accuracy is 0.81.
```

g) *Test the category classifier and end result*

Test image into the category classifier

An image with water is given as input to the trained network. This input is sent into the Category classifier. The image fed to the trained network is displayed.

Figure 63: Test image of a machine learning network

End result

The output that appears as ‘water’. It means that the image which was fed into the trained network has water. So, the classification of image was done properly. And the result obtain is correct. There are various examples discussed in the section 5.4.2. and an example for one of the outputs is as follows

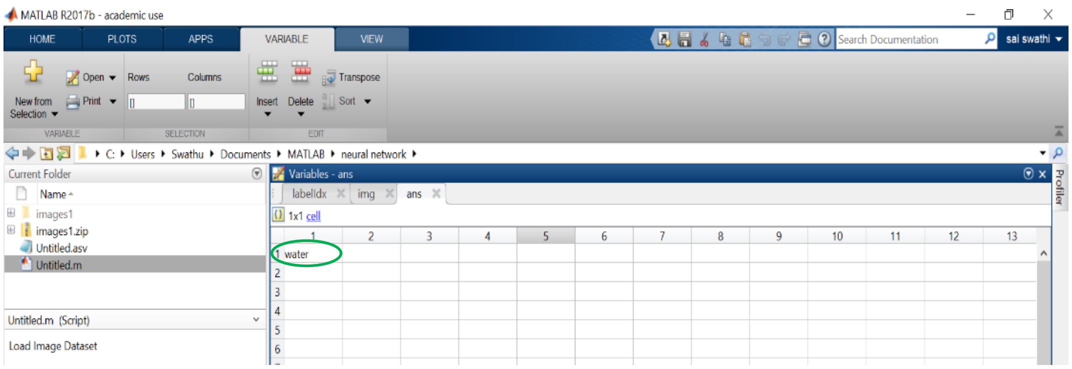


Figure 64: Output of machine learning network

5.4.2 Comparison of Results

The accuracy of classification between image classification algorithm with gray scale images and machine learning is presented below.

Table 12: Comparison of image classification algorithm with grayscale images and machine learning algorithm

Images	Image classification (Gray scale images)	Machine Learning
Image 1(no water)	Correct (TN)	Correct (TN)
Image 2 (no water)	Correct (TN)	Correct (TN)
Image 3 (water)	Correct (TP)	Correct (TP)
Image 4(no water)	Correct (TN)	Wrong (FP)
Image 5(water)	Wrong (FN)	Correct (TP)
Image 6(water)	Correct(TP)	Correct (TP)
Image 7(water)	Correct (TP)	Wrong (FN)
Image 8(no water)	Correct (TN)	Correct (TN)
Image 9(no water)	Correct (TN)	Correct (TN)
Image 10(water)	Correct (TP)	Correct (TP)
Image 11(no water)	Correct (TN)	Correct (TN)
Image 12(no water)	Wrong (FP)	Wrong (FP)
Image 13(water)	Correct (TP)	Correct (TP)
Image 14(no water)	Correct (TN)	Correct (TN)
Image 15(no water)	Correct (TN)	Wrong (FP)
Image 16(water)	Correct (TP)	Correct (TP)
Image 17(water)	Wrong (FN)	Correct (TP)
Image 18(water)	Correct (TP)	Correct (TP)
Image 19(water)	Wrong (FN)	Wrong (FN)
Image 20(no water)	Correct (TN)	Correct (TN)

Examples

Case 1:

Table 13: Correct Image classification(Gray scale) and correct machine learning

Algorithm	**Image classification (Correct)** **Machine learning (Correct)**
Image (no water)	

The image classification with grayscale images and machine learning algorithms classified the test image correctly. This test image has sand in it and there is no water.

Case 2:

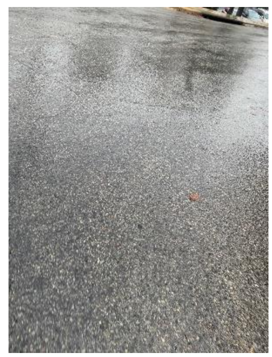
Table 14: Correct Image classification(Gray scale) and wrong machine learning

Algorithm	**Image classification (Correct)** **Machine learning (Wrong)**
Image (water)	

The image classification algorithm with grayscale images has classified the test image correctly, but the machine learning algorithms classified the test image incorrectly. The above test image has a white line and water. The test image looks glossier due to the presence of water. The machine learning algorithm might have not extracted these features. So, the machine learning algorithm detected this image inaccurately.

Case 3:

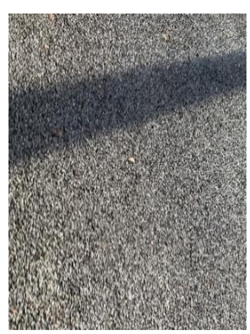
Table 15: Wrong Image classification(Gray scale) and correct machine learning

<table>
<tr><th>Algorithm</th><th>Image classification (Wrong)
Machine learning (Correct)</th></tr>
<tr><td>Image
(water)</td><td></td></tr>
</table>

The image classification algorithm with grayscale images has classified the test image incorrectly, but the machine learning algorithms classified the test image correctly. The top part of this image has water and other part appears to be dry. So, the image classification algorithm detected this image inaccurately.

Case 4:

Table 16: Wrong Image classification(Gray scale) and wrong machine learning

<table>
<tr><th>Algorithm</th><th>Image classification (Wrong)
Machine learning (Wrong)</th></tr>
<tr><td>Image
(no water)</td><td></td></tr>
</table>

The image classification and machine learning algorithm classified the test image incorrectly. In the above test image, it can be observed that a shadow of the pole is present. Also, some part of the image appears to be dark as if it has presence of water.

From the table 15 and the formula 1 in section 4.2.2 , the accuracies of the image classification and machine learning algorithms can be calculated.

i. Accuracy of Image Classification Algorithm(Gray scale)

Table 17: Accuracy of Image classification Algorithm(gray scale)

	No Water	**Water**
No Water	9 (TN)	1 (FP)
Water	3 (FN)	7 (TP)

Accuracy of Image classification Algorithm(Gray scale) = 80%

ii. Accuracy of Machine Learning Algorithm

Table 18: Accuracy of Machine Learning Algorithm

	No Water	**Water**
No Water	7 (TN)	3 (FP)
Water	2 (FN)	8 (TP)

Accuracy of Machine Learning Algorithm = 75%

6. CONCLUSION AND FUTURE WORK

Water detection through image data sets is considered in this research. The image datasets are created with the images that are captured using mobile camera. Images are not imported from any predefined libraries. The images in data set are captured in different climatic conditions like sunny, cloudy and rainy. A count of 96 images were considered under each category, these images are given as inputs to the algorithms. MATLAB software used to process these images.

The image classification algorithms are presented to detect the presence of water on the roads. An image classification algorithm was designed for water detection. The main features of an image like mean and standard deviation are extracted to perform classification. An image classification algorithm for gray scale images and color images was developed. The image classification algorithms under different color conditions and different image sizes were considered to test the formation of clusters. In addition to this algorithm, a machine learning algorithm was adopted. The concept of neural networks is used for classification. The machine learning algorithm concentrates on bag-of-visual words concept to differentiate images. Machine learning toolbox in MATLAB is used for this technique.

The machine learning classifier classified “no water” condition correctly while it failed in “water” condition. The image classification algorithm with color images has better accuracy overall when compared with the image classification algorithms with gray scale. Machine learning technique were partially successful in categorizing the images. The image classification algorithm performed better when compared to the machine learning algorithm. Under few circumstances, the image classification is a difficult task to execute. The results might be inaccurate when an image from other sources is given as test image for classifying. The trained database in image classification system has the images that are captured using mobile camera. As a result, it might be a difficult task for the classification system if an image from any other source is fed. The result of the machine learning technique might not be predicted right since the bag-of-visual words extracts its own features without predefining them.

The image classification algorithm for gray scale images and color images was trained with defined set of images. The mean and standard deviation values did not form any clusters in any of the conditions. If there were any different clusters formed the they would have been used for the classification of various conditions. So for these images the distance was measured to classify the images. One of the reasons for not formations of clusters is due to the image's histogram equalization in mobile camera and also the mean values and standard deviation values are not widespread.

The Machine Learning Algorithm was partially successful in classification. The no water case was successful while the other case was not successful. This provides a framework for future work. The image classification algorithm can be further enhanced by capturing the images with a digital camera and not by using mobile camera and also by combining with deep learning methodology. For deep learning, GPU's can be used to improve the time taken for computational operations. The model can be trained using larger datasets which can improve result accuracy. Each climatic condition can be assigned to certain neural layers which can increase output performance. Further this can be embedded to a hardware system and can be implemented.

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