# CLASSIFICATION OF SUCCULENT PLANT USING CONVOLUTIONAL NEURAL NETWORK


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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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## APPROVAL

This Project/internship titled **"Classification of Succulent plant using Convolutional Neural Network"**, submitted byAshik Kumar Das, ID No: 161-15-7210 and Md. Asif Iqbal, ID No: 161-15-7407 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 06 December 2019.

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## DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Mr. Aniruddha Rakshit, Senior Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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# ABSTRACT

Succulent plant-like aloes have many medical uses. They use as a laxative, to treat joint pain, skin inflammation, conjunctivitis, hypertension, stress, etc. It keeps releasing oxygen all night where other plants release carbon dioxide at night. Classification of succulent plant is a challenging and important topic to solve for their complex shape and beauty. Deep learning approach has a strong ability to extract high-level features from a piece of an image. This paper will introduce a new dataset of succulent plant and all data of the dataset are real data. We apply deep convolutional neural networks (DCNNs) on our dataset. First of all, we use the open camera for data collection and the camera resolution is 640×480 in order that the size of our image is same. Then we collect all the data from different nurseries in Dhaka city. We choose 9 different classes of succulent plant. Our total image 3421 where training data set is 2612 and the test data set is 809. We have used three convolutional layers, three max-pooling layer, three dropout layer and we also have a fully connected layer. We have run 30 epoch in our model and our result is really good. We achieve 97.40% accuracy using our model which is the best of all previous.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

Plants are very useful for us in many ways they give us oxygen through photosynthesis process. They also provide us with food and many other things. Plant reducing certain levels of pollutants, such as benzene and nitrogen dioxide and keep the air temperature down not just that reduce noise from busy road. We know there are many types of plants but we chose succulent plant because it looks very beautiful, grow slowly so space is usually not a problem, medically uses, and Purifies air rapidly, and removes formaldehyde. Most plants release oxygen during the day and at night they release carbon dioxide but succulent plant keep releasing oxygen all night [1]. A research of NASA found that succulent plant like snake plant and aloe Vera are capable of removing 87% of volatile organic compounds (VOC) [1]. In the library and study environment, they are extra helpful because VOC element like benzene and formaldehyde are found in books and ink [1]. Succulent plant-like aloes have many medical uses. They use as a laxative, to treat joint pain, skin inflammation, conjunctivitis, hypertension, stress, etc. [2]. They offer us a positive example by saving water and prospering in troublesome conditions, advising us that we are more grounded than we understand and even the most exhausting circumstances are not the stopping point [3].

Succulent plants have a worldwide conveyance and they normally come from the dry areas. It may store water in different structures, for example, leaves stems and roots [4]. It has a reputation for being easy to grow. In Africa, *Cotyledon Orbiculata* is known as "kanniedood", which means “cannot die” [5]. There are more than 30 botanical families of succulent plant from small and large trees [6]. Three types of succulent plants are used for trade, those are Cacti, Aloe and Euphorbia [7]. Because of their capacity to endure dry season conditions and the coming of reasonable warming required to develop these plants outside their regular range, succulent plants are especially supported as house plants [7]. They are popular for house gardening and prized by many plant gatherers because of their irregularity in nature. Identifying a succulent plant is very challenging for non-expert because there are many species that look similar [8]. There are some identification techniques like Visual Identification, Chemical Identification, and Genetic Identification. For Visual Identification plant's characteristics such as size, color, presence of spines, flower or leaf shape are used [7]. Characteristics of a flower is very important because sometimes using other features we can classify to genus or family level. Analyzing the Chemical synthesis of a plant it is possible to classify the plant as mass level. For Genetic Identification DNA pattern is used and it is possible to classify plant to species level [7].

### 1.2 Motivation

There are many types of succulent plant in the world and succulent plants are popular for their beauty and small size. People use succulent plant to decorate their home, room and working desk but peoples sometimes do not know the exact name of the plant which are growing in their garden. So it may difficult to take care of it. Therefor plant may die. Succulent plant has many medical uses just we have to know the proper name and have to use it properly. Some succulent plants are similar to see but their name is different and their use also. Therefor classification and identification of the succulent plant is essential. So our proposed method will be helpful.

### 1.3 Rationale of the Study

We use CNN to find succulent plant where many other plants in the world, size and type are totally different and of course this is the most beautiful plant in the world. Cacti, aloe plant and also orchids can be considered succulent plants. The succulent plant grows very slowly there for people keeps in room, office, working desk and decorate many other places for a long time. we are choosing this plant cause of don't need much water, can tolerate dry and the main part is the succulent plant used in medicine for example aloe is a succulent and the sap inside the leaves for helping with burns and used in cosmetics such as face creams. Some succulent plants are similar but the name is different and their use also. Therefore classification and identification of the succulent plant is essential for us. Overall this plant are helpful for us not harmful therefore we choosing a succulent plant.

### 1.4 Research Questions

- Why succulent plant are so popular?
- What is the difference between succulents and cacti?
- What temperature can they withstand?
- What is the amount of light needed to survive the succulent plant?

### 1.5 Expected Output

In this section, there are some points where has been told our expected outcome. The expected outcome of this research is to build an algorithm that will help to identify the succulent plant.

- The succulent plant can be classified.
- Succulent plant collector can be benefited by this.
- We can understand how much amount of care that the succulent plant needs.
- Succulent plants will be easy to identify.

### 1.6 Report Layout

Chapter one has expressed an introduction to the project with objective, motivation, Rationale of the Study, research questions, and expected outcome, this section describes the whole structure of this report.

Chapter two provide for the discussion on what already done in this succulent plant before. Then the later section of this second chapter shows, what is the limitation of this field? And we describe the challenges of this research from the beginning. Here discuss about research Summary, related work, different kind of problem and how we take challenges.

Chapter three is called research methodology. Here we will discuss about research subject and instrumentation, our data collection procedure, discuss about statistical analysis and how we implement the network using artificial neural network.

Chapter four is experimental result and discussion here describes our classification, work performance and experimental result. Some experimental pictures are also included in this chapter.

Chapter five is the conclusion here describe the summary of the study, implication for future work and conclusion the research paper and also included research references.

# CHAPTER 2

# BACKGROUND

## 2.1 Introduction

Succulent plant classification is one of the most challenging work because of their complex shape, beauty and their similarity. There are some authors whose work about plant classification, plant leaf classification, leaf disease and etc. So we are impressed to classify succulent plant using CNN. In this section, we will discuss about how work was related to our work, will give the summary of our work, what types of problem we have fatched and how we take the challenges complete this research. In related work section, we will discuss about some research paper which are related to our research. We will try to discuss about their work, their methods and their accuracy. In research summary section we will give the summary of related works. In the scope of the problem section, we discuss the problems which may occur in our research. We are the first who are going to classify succulent plant using the image so we have to face many challenges for this work. The machine has a need to learn about the different classes of succulent plant than it will be able to classify.

## 2.2. Related Works

For succulent plant classification and identification, we need to specify the plant from the image and then characterize color feature and shape feature. Anxiung et al. worked with flower image and to characterize the color features from flower image they proposed color histogram of ROI and two features sets like, Centroid-Contour-Distance (CCD) and Angle Code Histogram (ACH), used to characterize the shape features of a flower contour. They conducted their experiment using (I) color feature, (2) shape feature, (3) combined color and shape features to retrieve flower images. Then they compare the result with Swain's method result. And they want to say their result is better than Swain's method result [9]. N.Valliammal et al. classify plant through leaf image recognition. First, they capture RGB color image using a scanner or CCD camera then convert the colors from RGB to Gray. Secondly for preprocessing, use several techniques like boundary enhancement, smoothing, filtering, noise removal, etc. Thirdly for Feature Extraction they use border tracing algorithm. Fourth Image Segmentation, use Preferential Image Segmentation (PIS) method. From the resulting figure they want to say PIS algorithm is good for leaf and flower segmentation and object recognition from plants and set of flowers [10]. Shanwen et al. proposed a semi- supervised locally linear embedding (SALLE) and based on leaf images tried to classify plant by applying their proposed SALLE. They use Manifold learning method for feature extraction and selection & LLE method for avoiding the local minima problems. Used K-NN as a classifier. Their accuracy is greater than 90% on five kinds of plants. Future work: More difference leaf images can be classified, more features of the leaf should be included, and the proposed method should be extended to handle distortion problems [11]. M.-E. Nilsback et. al develop a visual vocabulary as object classifier that explicitly represents the various aspects like color, shape, and texture that distinguish one flower from another. The various stages of the classifier (vocabulary selection and combination) are each optimized on a validation set. They achieve a performance of 81.3% accuracy [12]. Fadzilah Siraj et. al use grey-level co-occurrence matrix (GLCM) and Law's Order approach for understanding flower image features. For predictive analysis they use Neural Network (NN) and Logistic regression. RGB color space image was transformed to HSV color space image for color extraction. The image surface is determined dependent on the grey-level co-occurrence matrix (GLCM). The accuracy of their work is average nearly 67% [13]. Marco Seeland et. al tried to improve image description methods. The author investigates from 1.detection, 2.extraction, 3.fusion, 4.pooling, 5.encoding of local features for quantifying shape and color information of flower images. 1) Multi-scale dense sampling (MSDS) is used dense sampling and patch size, Difference of Gaussians (DoG) as a detector for local features along with pixel-based and dense sampling. 2) Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG) methods. 3) bag-of-visual-words (BOW), Locality Constrained Linear Coding (LLC) methods. 4) Opponent SIFT and C-SIFT, SVM, MKL. They work on three different datasets: the Oxford Flower 17, the Oxford Flower 102, own Jena Flower 30. Gain 94% accuracy [14]. The author has presented a K-NN (k=3) density estimation framework with three features for species classification. They use WPROP method and PROP density estimator method. The WPROP method gives 96.69% accuracy and PROP method gives 96.81% accuracy. Their data set consists of 1,600 images of leaf specimens (16 samples each of one-hundred species) [15]. Enes Yigit et. al used artificial intelligence techniques (AIT) such as artificial neural networks, naive bayes algorithm, random forest algorithm, K-nearest neighbors (KNN) and support vector machine (SVM) are implemented to design an automatic identifier for the plant leaves. For this purpose, data of 637 healthy leaves consisting of 32 different plant species are used. The success rate is achieved as 88.6% by KNN technique and 94.2% by SVM technique [16]. Muammer Turkoglu et. al suggests the use of features extracted from leaves divided into two or four parts, instead of extracting for the whole leaf. Both the individual and combined performances of each feature extraction method (color features, vein feature, Fourier Description, Gray-Level Co-occurrence Matrix) are calculated by Extreme Learning Machine (ELM) classifier. They apply their suggested method on Flavia leaf dataset. The evaluated accuracy of the proposed method is 99.10%. The Flavia leaf dataset has 1907 leaf image from 32 different plant species [17]. G. Saleem et.al presented a new five-step algorithm (comprising image pre-processing, segmentation, feature extraction, dimensionality reduction, and classification steps) for recognition of plant type through leaf images. The algorithm is evaluated on ‘Flavia’ dataset of 1600 leaf images and on a self-collected dataset of 625 leaf images. With the proposed algorithm different classifiers were tested and the proposed technique with KNN classifier gives 98.75 accuracy and with naïve Bayes has shown the second-best accuracy of 93.95%, decision tree provides 90.56% and SVM provides 88.93% accuracy [18]. Belal A.M. Ashqar et. al present plant seedlings classification approach with a dataset that contains approximately 5,000 images with 960 unique plants that contain 12 species. Convolutional Neural Network (CNN) algorithms, a deep learning technique extensively applied to image recognition. They trained their model and achieved an accuracy of 99.48% on a held-out test set, demonstrating the feasibility of this approach [19]. Guillaume Cerutti et.al used some image processing technique like Image Segmentation, Contour detection, Image rotation to differentiate among different parts of a tree. To differentiate between foreground and Background used Naive Distance-based Classification for classification purposes. Leaf category (126 classes): Accuracy 85%. Fruit category (44 classes): Accuracy 50%. Stem category (78 classes): Accuracy 40%. Flower modality (139 classes): Accuracy 37%. [20]. The author has discussed many types of research in this field focusing on the used method and their Result. The author also discussed various techniques applicable for this problem. Many deep learning methods and their specialty have been discussed. Like ResNet, AlexNet, VGG 16, VGG 19, DenseNet, SqueezeNet, MXNet. Computer vision was also discussed in this paper [21].

## 2.3 Research Summary

Table 2.1: Comparison of proposed system with other studies.

| Author | Feature extraction phase | Classification phase | No. of species | No .of leaves | Accuracy (%) |
|---|---|---|---|---|---|
| Anxiung Hong, Zheru Chi, Gang Chen, Zhiyong Wung | From flower, characterize the color features | CCD, ACH | 14 | 885 | NULL |
| M. Seeland, M. Rzanny, N. Alaqraa, J. Wäldchen, P. Mäder | They investigate from 1.detection, 2.extraction, 3.fusion, 4.pooling, to 5.encoding of local features | MSDS, DoGSIFT, HOG, BOW, LLC | 250 | NULL | 94% |
| N.Valliammal and Dr.S.N.Geethalakshmi | Classify plant through leaf image recognition | PIS and WBV | NULL | 500 | NULL |
| Fadzilah Siraj, Muhammad Ashraq Salahuddin, and Shahrul Azmi Mohd Yusof | use gray-level co-occurrence matrix (GLCM) and Law's Order approach | CNN, GLCM | 30 | 1800 | 68.63% |

| | | | | | |
|---|---|---|---|---|---|
| C. Mallah, J. Cope, J. Orwell | K-NN(k=3) density estimation framework with three features for species classification | WPROP, PROP | 16 | 1,600 | 96.81% |
| H. Zhang, P. Yanne, S. Liang | Combines local texture features using wavelet decomposition and co-occurrence matrix of statistics and global shape features. | SVM | 32 | 1907 | 93.8% |
| Shanwen Zhang and Kwok-Wing Chau | Semi-SLLE (Supervised locally linear embedding) is proposed and applied to classify plant. | LLE, K-NN | 20 | 256 | 90% |
| Enes Yigit, Kadir Sabanci, Abdurrahim Toktas and Ahmet Kayabasi | artificial intelligence techniques (AIT)) | ANN, naive bayes algorithm, random forest algorithm, KNN and SVM | 32 | 637 | 94.2% |
| Muammer Turkoglu and Davut Hanbay | leaves divided into two or four parts, instead of extracting for the whole leaf | ELM | 32 | 1907 | 99.10% |
| G. Saleem, M. Akhtar, N. Ahmed and W.S. Qureshi | five-step algorithm proposed for plant type recognition | KNN , SVM | 57 | 2225 | 98.8% |

| | | | | | |
|---|---|---|---|---|---|
| | through leaf images | | | | |
| Belal A.M. Ashqar, Bassem S. Abu-Nasser and Samy S. Abu-Naser | Plant seedlings classification | CNN | 12 | 5,000 | 99.48% |
| M.-E. Nilsback, A. Zisserman | Visual vocabulary (object classifier) that explicitly represents the various aspects (color, shape, and texture) that distinguish one flower from another. | SIFT, HSV, MR | 17 | 1360 | 81.3% |
| Guillaume Cerutti, Laure Tougne, Céline Sacca, Thierry Joliveau, Pierre-Olivier Mazagol, Didier Coquin and Antoine Vacavant | To differentiate among different parts of tree, To differentiate between foreground and Background. Naive Distance-based Classification: For classification purposes. | ReVeS | 126 | 5092 | 85% |
| J. Wäldchen, M. Rzanny, M. Seeland and P. Mäder | Plant species identification | ResNet, AlexNet, VGG 16, VGG 19, DenseNet, SqueezeNet, MXNet | 1600 | 220000 | 90% |

## 2.4 Scope of the Problems

- **Noise Removal:**

We collect data from different nurseries. All the nursery have a huge amount of plant so when we clicked a picture of our target object sometimes it gets appended to numerous unavoidable things. Sometimes we can see another succulent is in our target plant frame so we have to remove them manually.

- **Blurring:**

We always tried to blurry the background of the target image but sometimes our target image got blurry. So it makes the change of color of our target object. And it is hard to identify different part of the plant. For some images background of the target image was not blurry. If the image background is not blurry than it is hard to read the image. So had to solve the problem.

- **Image resizing:**

We always tried to take images at the same size. After taking image we can realize that all images are not in the same size. Therefore we needed to resize those. Actually, we did it manually.

- **Data training:**

First, the data were needed to be trained by our proposed CNN model. After that, we were matched with the given data.

**2.5 Challenges**

In this chapter, in the related work section, we have discussed some research paper. Most of the authors work with leaf image or flower to classify plants or flowers. There was no one who works to classify succulent plant using image dataset. We are the first, whose are classifying succulent plant using DCNN from image dataset. So our work was challenging. Data collection, data processing and dealing with the dataset was too hard. Train the dataset and test the dataset was also challenging. There was no dataset available of succulent plant And was no enough work done before. So we had to start our work with our own motivation.

# CHAPTER 3
# RESEARCH METHODOLOGY

## 3.1 Introduction

In this chapter, we are going to discuss about our workflow to classify succulent plant. CNN is one of the most popular approaches which is used to classify. We develop our own CNN model which consist of four-layer with one fully connected layer. We will discuss about our dataset which we made, data collection, data processing, data augmentation. We will discuss about graph, table, and mathematical equation which are relevant to our proposed model. We will also give a clear concept about statistical analysis and implementation requirement.

## 3.2 Research Subject and Instrumentation

Research subject is called a research area which is relevant to our research. Not only for implementation but also for collection data, processing data. Our research area is convolutional Neural Network. To know about CNN, we have to know about Artificial Neural Network firstly. Instrumentation means which technology and method we used. In this subsection, we will discuss those.

### 3.2.1 Artificial Neural Network

An artificial neuron network (ANN) is called neural network sometimes it's also called multi-layer perceptron. It is a computational model, which is based on the structure and roles of biological neural networks. It can be marked as an information processing model that is motivated by the way biological nervous system, like how the brain process information. The main element of the model is the new structure of the information processing system. There is a large number of highly interconnected processing elements, which are working together to solve specific problems. The main advantage of ANN is achieved when simple artificial neurons are combined. These neurons are connected between them and they are structured in layers. The layers are divided into mainly three basic types. They are input layers, hidden layers, and output layers. The input layer receive the data. It could be compared with the input vector of other methods, not much calculation is done on this layer. This layer is connected to a hidden layer that is the one that is not in extremes. This is where their name comes, as they are not visible to the outside. The hidden layer provides encoding or internal representation of the input pattern so that the model can learn and maintain the relationship between the input pattern and output pattern in an effective way. There can be multiple hidden layers each of them connected to the previous one. When there is more than one hidden layer, the network is referred to as the deep neural network. Every neuron in the hidden layers and output layers is traditionally connected to all the previous layer. Finally, the last layer is called the output layer. It delivers the result of the ANN mode and it gives one output per class. This is important as ANNs are mostly used for the classification problem.

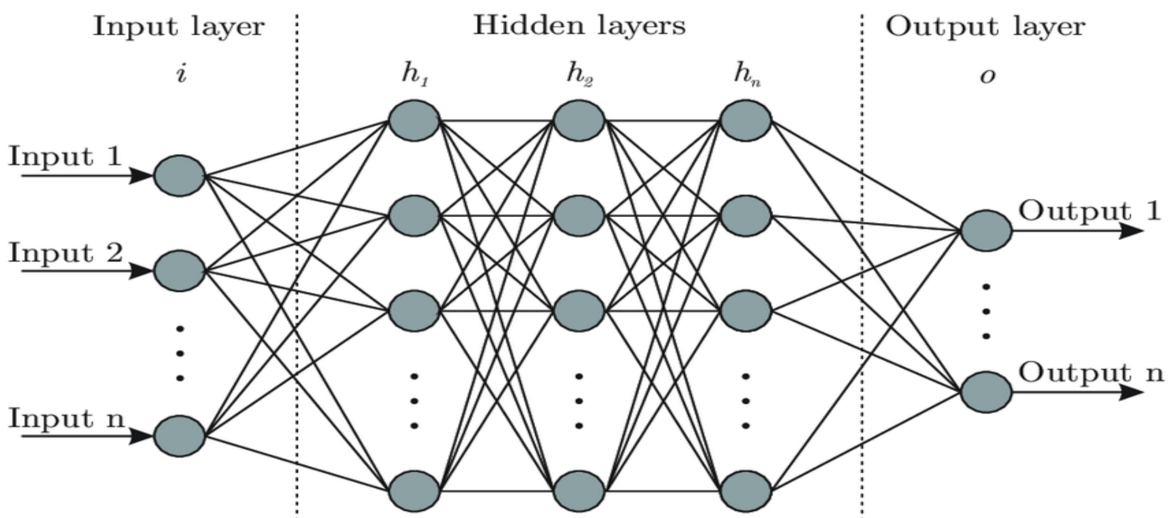


Figure 3.1: A general architecture of ANN

Artificial Neural Network use different types of activation function. In the sub section we will discuss about some activation function.

#### 3.2.1.1 Activation Functions

The activation function is used to prepare the output of neural network as yes or no. It makes the value of result in between 0 to 1 or -1 to 1 etc. and it depends on the type of activation function. Activation function is divided into two categories. One is the linear activation function and another is non-linear activation function. In linear activation functions, the output of the function will not be limited between any ranges. It does not help with the complexity of multiple parameters of common data that is served to the neural networks. On the other hand, the nonlinear activation function produces it easy for the model to generalize and modify to a variety of data. This is the reason that non-linear activation functions is the most used activation function. Some non-linear activation function is discussed below.

- **ReLU (Rectified Linear Unit) Activation function:**

The ReLU is an activation function and it is using the most in the world now. Almost all the convolutional neural network is using it. It is efficient and it can converges much faster than most other activation functions [22]. The ReLU function can be mathematically defined as:

$$f(x) = \max(0, x) \tag{3.1}$$

The ReLU is half rectified, here f(x) will be zero when x will be less than zero and f(x) is equal x when x is larger or equal to zero. It ranges from zero to infinity. Some pros and cons of ReLU are described below.

- It was found to extraordinarily quicken the intermingling of stochastic slope drop contrasted with the sigmoid function.
- Compared to sigmoid neurons that involve expensive operations (exponentials, etc.), the ReLU can be actualized by essentially thresholding a grid of initiations at zero.
- Unfortunately, ReLU units can be delicate during preparing and can "pass on".

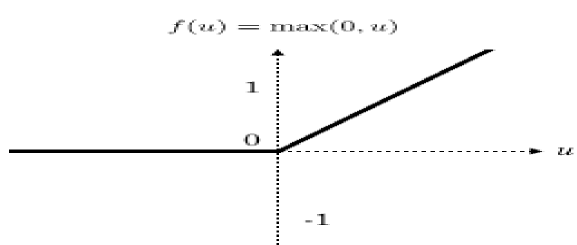


Figure 3.2: ReLU activation function [23].

- **Softmax Activation Function**

Softmax work [24] is a fascinating actuation work that transforms numbers otherwise known as logits into probabilities that total to one. Softmax capacity yields a vector that speaks to the likelihood circulations of a rundown of potential results. It's additionally a center component utilized in profound learning grouping errands. Softmax function outputs numbers that represent probabilities, each number's value is between 0 and 1 valid value range of probabilities. The range is denoted as [0, 1]. The numbers are zero or positive. The entire output vector sums to 1. That is to say, when all probabilities are accounted for, that's 100%. The softmax activation function is a more generalized version of the sigmoid activation function used for multiclass classification problem.

Table 3.1: Conversion of logit score into probabilities via softmax activation function

| Logits Score | SoftMax | Probabilities |
|---|---|---|
| $y = \begin{cases} 2.0 \\ 1.0 \\ 0.1 \end{cases}$ | $S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$ | $\begin{cases} p = 0.7 \\ p = 0.2 \\ p = 0.1 \end{cases}$ |

### 3.2.1.2 Loss Function or Error Functions

Loss function plays an important role in the artificial neural network that is used for measuring the inconsistency between the actual value and predicted value. It is a non-negative value, where the robustness of the model increases with the decrease of the value of loss function. The loss function is the hardcore of empirical risk function as well as a significant component of the structural risk function. Neural networks are trained using stochastic gradient descent and require that you choose a loss function when designing and configuring your model. Different kind of loss function is discussed below.

- **Cross-Entropy**

Cross-Entropy [25] or Binary Cross Entropy is also called logarithmic loss and used for binary classification problem. Cross-entropy mainly measures the divergence between two probability distribution, if the value of cross-entropy is large, which means that the difference between two distribution is large, on the other hand, if the cross-entropy is small, which means that two distribution is similar to each other. Cross-Entropy can be mathematically defined as the following equation, where the symbols bear their usual meaning.

$$L = -\frac{1}{n}\sum_{i=1}^{n}( y_i \log(\hat{y}_i)) + (1 - y_i) \log(1 - \hat{y}_i) \qquad (3.2)$$

Cross-entropy doesn't suffer from slow convergence while using a sigmoid activation function. Cross-entropy offers more training than Mean square error. So using Cross-entropy as loss function is more preferable than mean squared error.

#### 3.2.1.3 Learning or Training of Neural Network

The ability that makes neural network different from other computation method is its ability to learn from examples. It can automatically find the pattern if enough data is given. In this section, we will briefly discuss how a neural network is trained from example specifically how the weights are updated so the neural network can learn the mapping for specific input and its corresponding output.

#### 3.2.1.4 Different Types of Optimizer for Gradient Descent

The role of the optimizer or optimization algorithm for gradient descent is to reach the global minimum faster and efficient way such that it does not get stuck in the local minima. Different type of optimizer for gradient descent is discussed below.

- **RMSprop**

RMSprop or Root Mean Square Propagation has an interesting history. It was contrived by the unbelievable Geoffrey Hinton while proposing an irregular thought during a Coursera class [26]. RMSprop and Adadelta have both been developed independently around the same time stemming from the need to resolve Adagrad's radically diminishing learning rates. RMSProp also tries to dampen the oscillations, but differently than momentum. RMSprop likewise removes the need to alter the learning rate and does it consequently.

- **Adam**

Adaptive Moment Estimation (Adam) [27] is another technique that registers versatile learning rates for every parameter. Notwithstanding putting away an exponentially rotting normal of past squared slopes like Adadelta and RMSprop, Adam additionally keeps an exponentially rotting normal of past inclinations, like force. While force can be viewed as a ball running down an incline, Adam carries on like an overwhelming ball with grating, which along these lines favours level minima in the error surface [28]. Adam improvement calculations join the heuristics of both Momentum and RMSProp. While momentum accelerates our search in direction of minima, RMSProp impedes our search in the direction of oscillations. Adam optimization algorithm tries to combine both.

### 3.2.1.5 Dropout

The term "dropout" refers to dropping out units (both hidden and visible) in a neural network. Dropout is an extremely effective, simple and recently introduced regularization technique [29]. Dropout refers to ignoring units during the training phase of a certain set of neurons which is chosen at random. During the training phase, for each hidden layer, for each training sample, for each iteration, ignore (zero out) a random fraction, p, of nodes (and corresponding activations). During the testing phase, Use all activations, but reduce them by a factor p (to account for the missing activations during training).

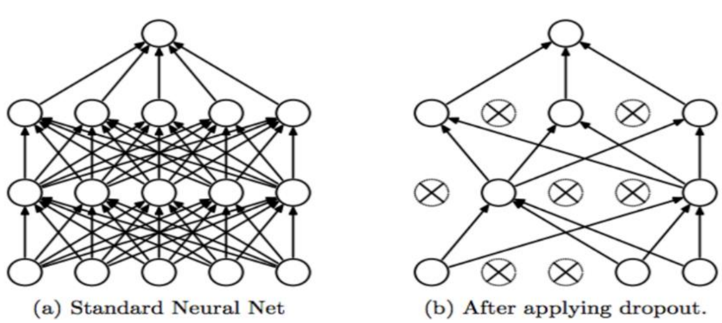


Figure 3.3: Dropout used in a network.

### 3.2.2 Convolutional Neural Networks (CNN)

In computer vision, images are the training data of a network and the input features are the pixel of an image. These features can get huge. For example, when dealing with a 2 megapixel RGB image, the total number of feature is 6 million. Then if passing this through an artificial neural network or multi-layer perceptron with 1000 hidden units, we end up with some weights of around 6 billion parameters. These huge number of parameters are very difficult to train and manage. In order to solve this problem Convolutional Neural Network or ConvNets has been introduced.

Convolutional Neural Networks (CNN) behaves in a similar way to the ordinary Artificial Neural Network discussed before. CNN is also made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. The whole network expresses a single differentiable score function: from the raw image pixels on one end to class scores at the other. And they use a loss function on the last (fully-connected) layer just like an ordinary neural network. The main difference is ConvNet architectures make the explicit assumption that the inputs are images, which allows the model to encode certain properties into the architecture. These then make the forward function more efficient to implement and vastly reduce the number of parameters in the network.

#### 3.2.2.1 Layers of CNN

Convolution Neural Network mainly consists of 3 types of Layer. The first one is the convolutional layer in which the input image is convoluted with a number of filters in order to produce feature maps. The second one is pooling layer in which translation and scale invariance are provided. This layers also reduces the computational complexity by decreasing the size of feature maps. Finally, there is a fully connected layer that is basically the same as a hidden layer in the neural network. It tells us what features exist in an image or not.

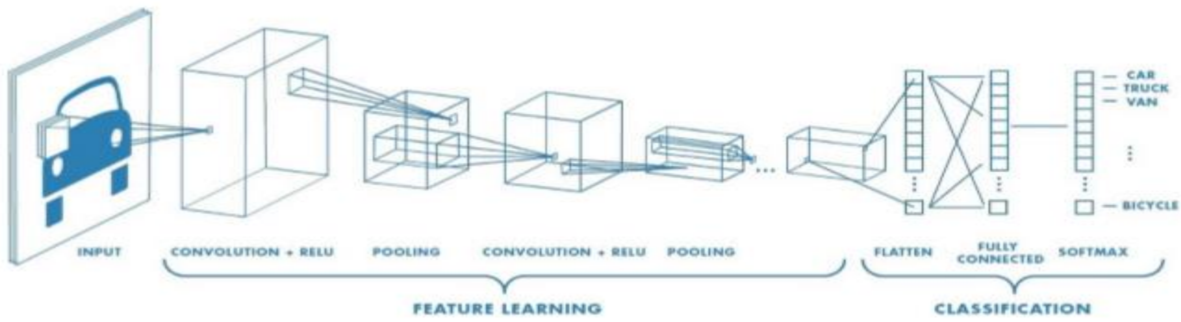


Figure 3.4: A typical CNN architecture [30].

This above figure describes the CNN architecture for a conventional image recognition task. In this network two convolutional layers and two pooling layers have been used. In convolutional layer, ReLU activation function has been used for adding non-linearity in the feature maps. After the convolutional and pooling layer, the extracted feature maps have been flattened via a fully connected layer and sent to multi-layer perceptron for classification. In most of CNNs, the softmax activation function is used in the output layer for predicting the probability of the result.

To understand the convolutional operation in details in CNN we need to understand some basic terminology which is discussed below.

- **Kernel Size**

The width and height of the receptive field for the neurons in the stack. We mostly use square kernels in which both sides are usually of equal size.

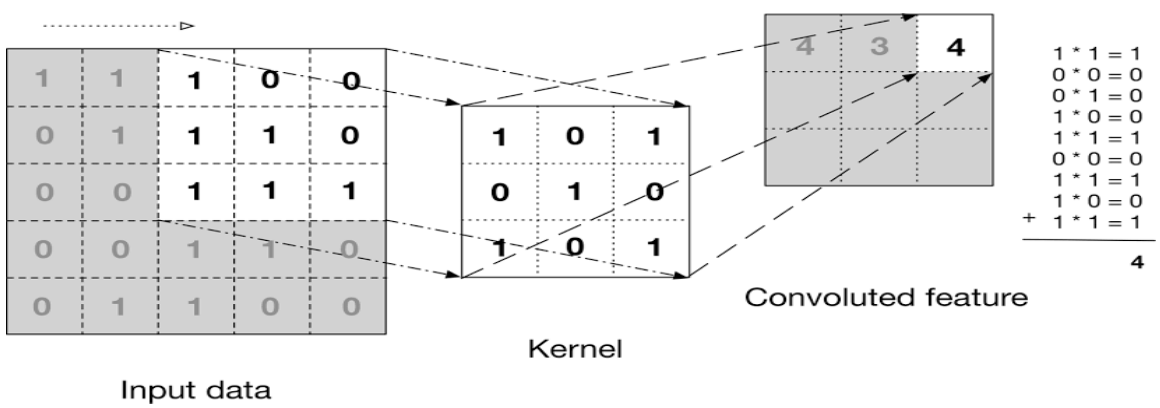


Figure 3.5: 3x3 kernel

- **Stride**

Each neuron processes a region of the input space. As these regions can overlap, the stride indicates the distance between their centres. As such, a stride of 1 means that each neuron processes the same region as their neighbour except for one column. The larger the stride the smaller the output width and height of that layer.

- **Padding**

In some cases, the neuron at the border of the layer cannot process a whole receptive field. This may happen due to stride. In order to address this issue, one possibility is to add a border around the image of 0’s. This way it can be guaranteed that all neuron process a complete receptive field. The padding if used is usually 1 or 2.

- **Number of kernel**

It corresponds to the number of filters that are being used to each learning to look for something different in the input.

**3.2.2.2 Max Pooling:**

A spatial neighborhood is defined and as sliding through the input largest element is taken with the region covered by the spatial neighborhood or filter. Max Pooling also performs as a Noise Suppressant. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction.

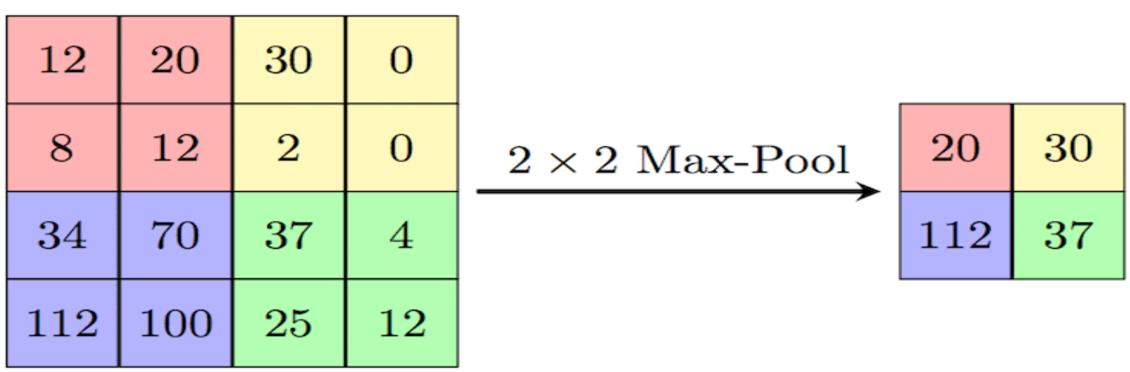


Figure 3.6: 2x2 Max pooling

#### 3.2.2.3 Fully-Connected (FC) Layer

Fully-Connected Layer is artificial neural layers connected to all neuron from the previous layer as ANN. They do not use any of the introduced parameters, they only use the number of the neuron. Adding a Fully-Connected layer is a general way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The Fully-Connected layer is learning a possibly non-linear function in that space.

### 3.2.3 Workflow

There are some steps in our workflow those are data collection, data processing, data resizing, train and test data, evaluation, recognize, Conclusion.

**Step 1- Data collection:** data collection was one of the most challenging work for us. There was no dataset available about our work. We collect data from different pleases. And make our own dataset by making different classes and give them data.

**Step 2- Data resizing:** we always tried to keep the data size same. But we failed to do it. For some images we can see that the image size is not same. So we resize them manually.

**Step 3- Train and test data:** we make two set of data one is train set another is test set. Then we train the machine by train set and test the accuracy by test set. We select our own CNN model to train and test our dataset. There are more than five hundred hidden layer in our proposed CNN model.

**Step 4- Evaluation:** All the result has been discuss in this section with graph. We discuss train accuracy, test accuracy, validation loss with graph and accuracy. With figure we also discuss our confusion matrix.

**Step 5- Recognize:** After train, test and evaluation, it is time to data recognition. There are classes of data and our model can recognize all of them.

**Step 6- Predict and Accuracy:** After all work we achieve our model accuracy. Our model can predict data and give good accuracy.

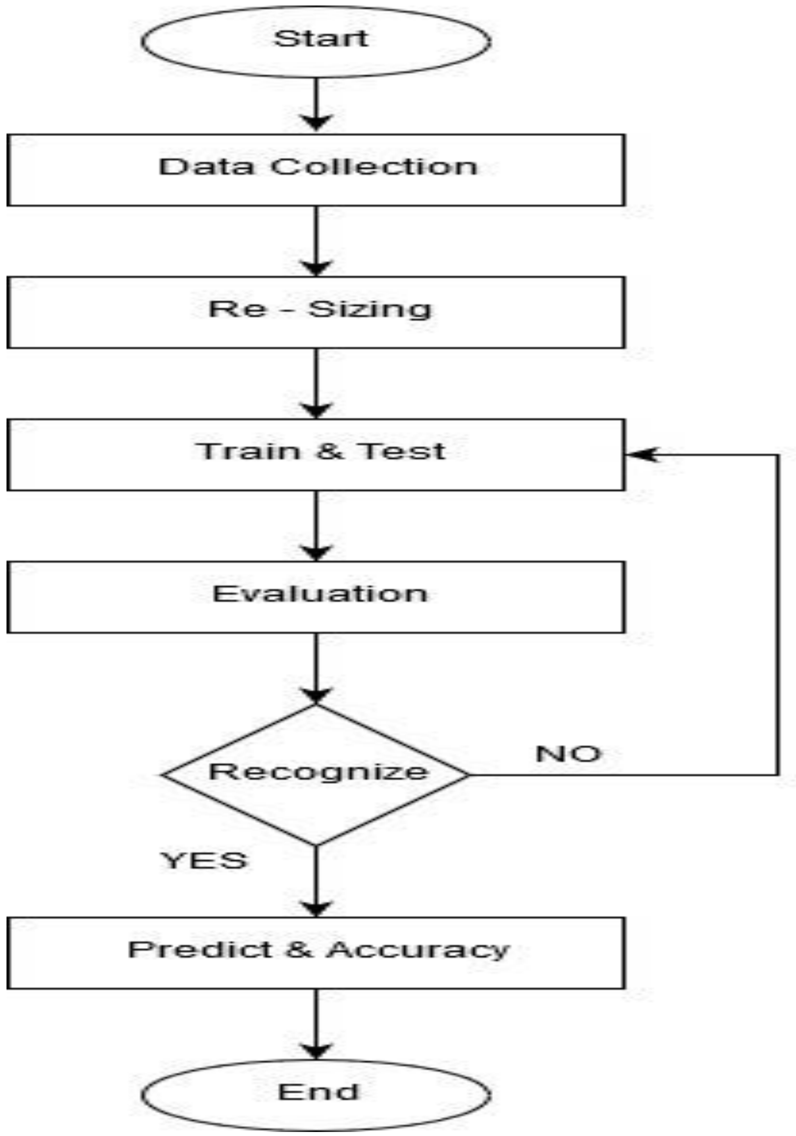


Figure 3.7: workflow diagram

### 3.2.4 Proposed model

We proposed a CNN model to classify succulent plant. There are four convolutional layers and one fully-connected layer in our proposed model. Our first convolutional layer is input layer and its padding is same, the filter size is 32 with 3x3 kernel and its input size is 32x32 with RGB color mode. In the layer, ReLU activation function is used. Working principle of Rectified Linear Unit (ReLU) function [31] is, it takes all positive and negative number as an input than if the number is positive, gives the same number as output but if the input number is negative, it gives zero as output. Actually, it replace negative by zero.

The output of the first layer go through the first max-pooling layer. Max-pooling layer is used to reduce the parameters [32]. From each region, it takes the max number for the sub-regions. Here the max-pooling layer contains pool size 2 and strides 2 and the output goes through 25% dropout [33] layer.

Filter size of the second convolutional layer is 64 with 3x3 kernel and its padding is same and strides 1. This layer has a batch normalization [34] to increase the stability of the convolutional network. It can reduce the training time and make higher performance by disappearing gradient. To makes the learning procedure speedier and utilizing the higher learning rate batch normalization used here. The result of this layer goes through another layer which is as like as this layer and the result go through next max-pooling layer which contains pool size 2x2 and strides 1x1 than the result go through another 25% dropout layer.

The output of the second layer is the input of the third layer. Filter size of our third convolutional layer is 128 with 3x3 kernel, same padding with 1x1 strides. The output go through batch normalization and max-pooling layer as like a previous layer than go through another 25% dropout layer.

Layer four holds 256 filter size with 3x3 kernel and other properties of this layer like padding, strides, batch normalization and activation, max-pooling, dropout are same as the previous layer.

After all four-layer, there is a fully connected layer. There is another name of a fully connected layer that is dance layer. Our fully connected layer has 512 hidden nodes with batch normalization and activation with a 50% drop out. Another dance layer has 9 nodes with SoftMax(3.3) activation.

$$\sigma(z)_i = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}} \text{ For } i = 1\ldots \text{ k and z} = (z_1, \ldots., z_k) \in \mathbb{R} \qquad (3.3)$$

Model: "sequential_2"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d_7 (Conv2D) | (None, 32, 32, 32) | 896 |
| activation_8 (Activation) | (None, 32, 32, 32) | 0 |
| max_pooling2d_5 (MaxPooling2 | (None, 16, 16, 32) | 0 |
| dropout_6 (Dropout) | (None, 16, 16, 32) | 0 |
| conv2d_8 (Conv2D) | (None, 16, 16, 64) | 18496 |
| batch_normalization_7 (Batch | (None, 16, 16, 64) | 256 |
| activation_9 (Activation) | (None, 16, 16, 64) | 0 |
| conv2d_9 (Conv2D) | (None, 16, 16, 64) | 36928 |
| batch_normalization_8 (Batch | (None, 16, 16, 64) | 256 |
| activation_10 (Activation) | (None, 16, 16, 64) | 0 |
| max_pooling2d_6 (MaxPooling2 | (None, 8, 8, 64) | 0 |
| dropout_7 (Dropout) | (None, 8, 8, 64) | 0 |
| conv2d_10 (Conv2D) | (None, 8, 8, 256) | 147712 |
| batch_normalization_9 (Batch | (None, 8, 8, 256) | 1024 |
| activation_11 (Activation) | (None, 8, 8, 256) | 0 |
| max_pooling2d_7 (MaxPooling2 | (None, 4, 4, 256) | 0 |
| dropout_8 (Dropout) | (None, 4, 4, 256) | 0 |
| flatten_2 (Flatten) | (None, 4096) | 0 |
| dense_3 (Dense) | (None, 512) | 2097664 |
| batch_normalization_10 (Batc | (None, 512) | 2048 |
| activation_12 (Activation) | (None, 512) | 0 |
| dropout_9 (Dropout) | (None, 512) | 0 |
| dense_4 (Dense) | (None, 9) | 4617 |

Total params: 2,309,897
Trainable params: 2,308,105
Non-trainable params: 1,792

Figure 3.8: Representation of model summary

### 3.2.5 Learning rate and Optimizer of the model:

The rate in which the weights of the neuron or nodes are updated is known as the learning rate. The learning rate is an important factor if the learning rate is too small, it will take more time to converge on the other hand if the learning rate is too large it may overshoot the global minimum. The learning rate needs to be controlled as the effects of different learning rates can produce different results and the goal is to minimize the loss function.

The optimization algorithm is very important in machine learning and computer vision work. It can change the result and make it really adequate. With learning rate 0.0001, our proposed method uses Adam optimizer.

### 3.2.6 Data augmentation

We used a data augmentation technique to avoid overfitting and expend the dataset artificially. It increases the value of base data by including data got from inside and outside sources within a venture. It helps to get batter result by increasing data of the dataset. There are some data augmentation technique. We augmented our data by rotating 20 degree, shifting high and width rage, by rescaling, zoom. Data augmentation method which we used, are given below

- Rotate data 20 degree randomly
- Shifting height of images 20%
- Shifting width of images 20%
- Rescaling 1/255
- Shear range 20%
- Zoom the images 20% randomly
- Adding horizontal flip
- Nearest fill mode

We used those technique for train data and test data also.

### 3.2.7 Training the Model

Adam Optimizer is used to compile our model. In our dataset there are total 3421 data. There are 76% data in train set and rest of data in test set. From test set and train set we get some data in validation set. We use batch size 30 and we have train the network for 30 epochs.

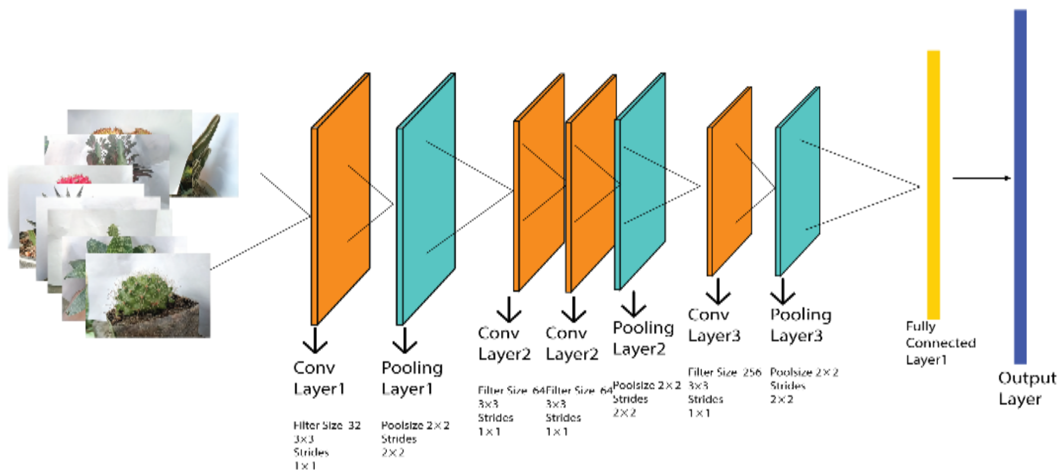


Figure 3.9: Our proposed CNN model

## 3.3 Data Collection Procedure

In this section, we will discuss our dataset and data collection process.

### 3.3.1 Dataset

We have made a dataset of more than 3421 images. Our data set contains 9 different classes of succulent plant. We have collected all data from different nurseries from inside and outside Dhaka city so data collection was very challenging. We took 2612 images in the training set and 809 images in the test set.

### 3.3.2 Data collection

We have used our mobile phone for data collection. Firstly we install Open Camera app from Google play store and fixed camera settings. We always tried to fix the camera resolution of 640x480 in order that the size of our image is right. We always tried to fix the photo mode STD. we fixed the white balance Auto, scene mode Auto and color effect none. We did not use any photo gird. We fixed the focus for continuous picture.

**Camera settings:**

- Resolution: 640x480
- Photo mode: STD
- White balance: Auto
- Scene mode: Auto
- Color effect: None
- Photo gird: None
- Focus: continuous picture

We collect all data in the dataset from different nurseries. In Dhaka city, there are some large and small nurseries. We go there and capture picture of our target succulent plant. There is a matter of sorrow that all the owner of the nurseries did not give permission to capture the image. Another problem was if one nurseries have two or three classes of succulent plant than another did not have those. We used extra white paper for removing background noise. So our data collection was challenging.


Figure 3.10: Some data of our dataset

### 3.3.3 Data preparation:

When we were collecting data we always tried to fix the camera resolution, therefore, the size of our image is equal in size. But after collecting we can see that the size of all image was not the same. So we had to resize the images. In some case, we noticed that there was noise in the images. In that case we removed that manually. Finally, make all the images in same resolution 640x480. And tried to give the same number of images in each class.

### 3.4 Statistical Analysis

An error of the training set of data is called training loss. After running the validation set of data through the trained network we get some error. The error is called validation loss. By increasing epochs train error and validation error drop. With the drop of train loss and validation loss, train accuracy and validation accuracy increase rapidly. In the figure 3.11 we can notice our training loss and validation loss. And in the figure 3.12 we can notice our training accuracy and validation accuracy.

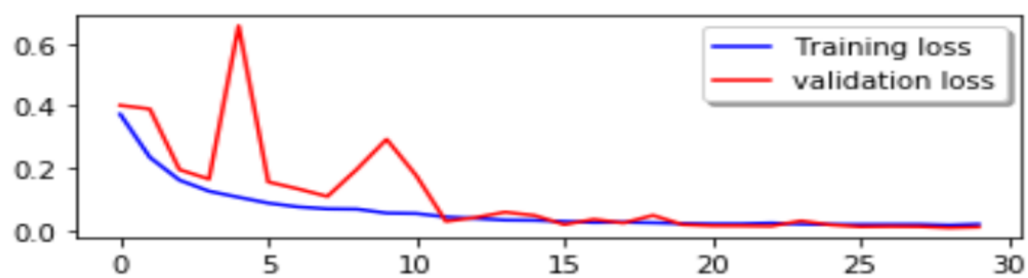


Figure 3.11: Training & Validation loss

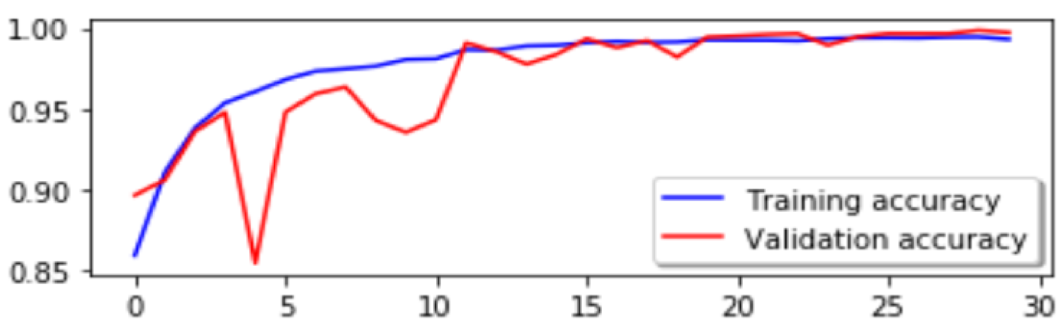


Figure 3.12: Training & validation accuracy

### 3.5 Implementation Requirements

After the best possible examination on all important factual or hypothetical ideas and techniques, a rundown of necessity has been created that must be required for such a work of Image Classification. The important necessary things are given below:

**Hardware/Software Requirements**

- Windows Operating system (Windows 7 or above)
- Hard disk (Minimum 500 GB)
- RAM (Minimum 4 GB)

**Developing Tools**

- Python Environment
- Google Colab

## CHAPTER 4

## EXPERIMENTAL RESULTS AND DISCUSSION

### 4.1 Introduction

Result and Performance evaluation of a model is a crucial part of the classification task. In the previous chapter, the proposed methodology and implementation process for Succulent plant classification is described. In this chapter, we will discuss about our experimental result.

### 4.2 Experimental Result

A survey of prognostication results on a classification problem is called a confusion matrix. The number of correct and incorrect prognostications are reviewed by each class with count values and broken down. This is the core to the confusion matrix.

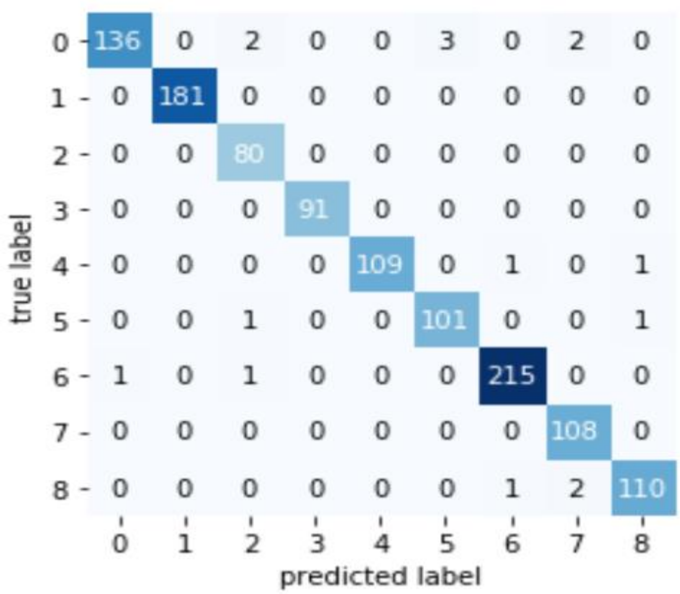


Figure 4.1: Confusion Matrix

We have used the average accuracy performance metric based on the confusion matrix. Confusion Matrix has four components True Positive (TP), False Positive (FP), False

Negative (FN) and True Negative (TN). Accuracy can be measured as the following equation:

**Precision:** precision is calculated by using TP and FP value. Precision value of our model is 0.975029.

$$Precision = \frac{TP}{TP+FP} \tag{4.1}$$

**Recall:** The value of recall is calculated using TP and FN value. Recall value of our model is 0.974042.

$$Recall = \frac{TP}{TP+FN} \tag{4.2}$$

**F- Score:** Using the value of Precision and Recall we can calculate the f-score value.

$$F - Score = 2 * \frac{Precission * Recall}{Precission + Recall} \tag{4.3}$$

**Accuracy:** Accuracy is calculated by using all TP, TN, FP and FN values. Here is the equation. Accuracy of our model is 97.40%.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.4}$$

### 4.3 Descriptive Analysis

First, we collect data for our dataset then we divide the data as train and test data. For train set, we give 76% data and the rest of the data of the dataset are given in the test set. We establish a CNN model to classify succulent plant. Then we train and test our data using our CNN model. In our dataset there were nine classes of data. The result we get is really good. If our dataset had more data, the result would be better.

### 4.4 Summary

We use some library function for the preretirement of the code. Make the data set by collecting data and read them train and test. From the figure of training loss and validation loss, training accuracy and validation accuracy, we can see the result is good. We get the accuracy of 97.40% which is good.

## CHAPTER 5

## SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION, FOR FUTURE RESEARCH

### 5.1 Summary of the Study

Succulent is important to us for its diverse feature. But it is a matter of sorrow that there is no one who has worked with the succulent plant. Some people have worked with plant leaf, plan deceases. We are the first who tried to classify succulent plant using an image data set. The main goal of this research work is to provide an accurate and efficient classification of succulent plant. We have worked with nine classes of succulent plant. There was total 3421 data in our data set. The classes was Acanthocereus tetragonus, Euphorbia lactea, Euphorbia Trigona, Haworthiopsis Limifolia, Hoya Kerrii, Sansevieria Trifasciata, Gymnocalycium Mihanovichii, Huernia macrocarpa, Mammillaria compressa. All data of our dataset was collected from different places. In our train set, there are 2612 image data and in our train set there are 809 image data. We develop a CNN model based on our own dataset. And the result of our dataset is good. We achieve 97.40% accuracy using our model.

### 5.2 Conclusion

In this paper, we proposed a way of succulent plant classification process by our CNN model. We have used three convolutional layers, three max-pooling layer, and three dropout layer in our model. We have also a fully connected layer. Dropout layer is used to reduce overfitting. We augmented data by some ways. We have run 30 epoch in our model. The result we have achieved is really good. The succulent plant is one of the most useable plants in the whole world. People are growing this kind of plant in there house, garden. Sometimes people use it to decorate their working or reading desk. Sometimes people cannot take the proper care of this plant. Therefor plant die. It people can know the real name of the succulent plant than it will be easy to take care of the plant. If we can take proper care this plant will be able to live long. Hopefully, our method will be helpful for plant gatherer and people who care about succulent pant.

### 5.3 Implication for Further Study

In our proposed method, we can classify the succulent plant. Here we used only nine class of data to classify. Our future goal is to work with more class of data and built a better neural network to get more accuracy. In future, we have a plan to make an android app which will be used to identify succulent plant. Using that app people will be able to capture the image and if the object is a succulent plant, our app will give details about the plant. It will show some similar images of the plant. Let us know the common name and scientific name also. And if the plant has any medical use, the app will give the use of the plant.

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