A MACHINE LEARNING APPROACH FOR VEGETABLE RECOGNITION

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APPROVAL

This Project/internship titled **“A Machine Learning Approach for Vegetable recognition”**, submitted by Md. Nasir Uddin, ID No: 182-15-11540, Md. Ashraful Alam, ID No: 182-15-11534, Abdullah Al Shafayet, ID No: 182-15-11607 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 09-September-2021.

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I hereby declare that, this project has been done by us under the supervision of**, Zerin Nasrin Tumpa, Lecturer, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

In perceiving objects in an image, computer vision and example recognition is an emerging territory. The advances in perceiving objects in pictures have a wide range of applications, including frameworks for discovering vegetables and natural products, vehicles, and other frameworks. Our research focuses on the discovery of vegetable varieties in order to create a reliable vegetable recognition system. Since the vegetables can appear the same due to shading and different highlights, such as red tomato and red capsicum having similar tones, using highlights to differentiate vegetables can result in false discovery, so this research proposes an intraclass vegetable recognition system based on profound learning. Three forms of vegetables were used. Those are Carrots, Tomatoes and Cauliflowers. By extracting and learning the images, profound learning had been used to classify the vegetable class, and the convolution neural network (CNN) was investigated. Intraclass vegetables were viewed accurately with 95.50% accuracy and proficiently using profound learning, according to the results of the evaluation.

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LIST OF ABBREVIATION

LSTM	Long Short Term Memory
RNN	Recurrent Neural Network
NLTK	Natural Language Tools Kit
NLP	Natural Language Processing
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
NMT	Neural Machine Translation

CHAPTER 1

1.1 INTRODUCTION:

One of the most important aspects of our daily lives is vegetables. It is a need for both humans and animals alike. Approximately ten thousand plant species are classified as vegetables around the world. All of these vegetables have about 50 or so significant plant species that are economically available. Vegetables must be categorized into subclasses or categories in order to be properly interpreted or discussed. Vegetables with identical characteristics and behaviors should be combined. There are several different types of classifications, such as botanical classification, which includes genus, species, family, class, subspecies, and so on, as well as life cycle, weather, and temperature classifications. There are several different types of classifications, such as botanical classification, which includes genus, species, family, class, subspecies, and so on, as well as classifications based on life cycle, weather or temperature, culture, and used plant parts, among others. [13]

The detection of vegetables is a common feature of vision-based strategies for identifying plants from videos or photographs. Deep learning algorithms are now widely used to classify numerous fruits and vegetables. The use of convolutional neural networks (CNN) to create a proper end-to-end classification method has always been the subject of recent detection and classification of vegetables. TensorFlow, SSD, SVM, You Look Only Once (YOLO), faster CNN (F-RCNN), and other major techniques are widely used in the context of vegetable detection and recognition systems. [14]

There are several automated systems for vegetable classification and detection around the world, but for this study, we will focus on Bangladeshi vegetables and their classifications. Since most farmers in rural areas are illiterate, they are unaware of the advanced technology available in the agricultural sector, which is one of the major barriers to adoption. Agriculture production is critical, and it should be attractive to the population in order to meet demand. This study includes a broad data set of different types of vegetation. We transformed the image into an array for feature extraction and used the CNN algorithm for classification to get the best results for this system.

1.2 MOTIVATION:

One of the most significant aspects in the present era is vegetation classification. Vegetation classification has a plethora of benefits. Many kinds of research have been executed with vegetable detection but those are not for our region. Moreover, the existing systems that have been implemented in the past have had weak results. As a result, we've chosen to focus our research on our native vegetables, which provide a more comprehensive set of data.

We chose to work on our regions vegetables for this research because the majority of people in Bangladesh depend on vegetation in some way, some for their livelihood and others to meet their nutritional requirements. This digitized method can be advantageous in a variety of different ways. This terrain's younger generation will be capable of learning about Bangladeshi vegetables and their classifications. They will be able to quickly determine which vegetable to use for which reason. This study will be extremely beneficial to the digitalization of vegetation.

However, after estimating the method's potential results, we chose to construct a framework that can correctly classify various vegetables and their subclasses. The main purpose of this study is to create an efficient framework with a large dataset that can generate a better vegetable identification system for Bangladeshi citizens.

1.3 RATIONALE OF THE STUDY:

There has already been a lot of research on vegetation categorization, but much of it has focused on foreign vegetation systems. Bangladesh has a population of approximately 164 million people, the majority of whom depend on vegetables to survive. In our country, nevertheless, there is no well-established system for classifying vegetables. Since Bangladesh is an agricultural country, many people rely solely on it. The government also wants the country to expand through agriculture because it is a developing country. As a result, a system for automatically identifying vegetables is needed.

In today's digital world, vegetation classification is incredibly important. The application of this technology can be helpful in a variety of ways, including government institutions, medical industries, Bangladeshi agricultural departments, supermarket automatic categorization, and so on. We are interested in learning more about how to improve the use of these kinds of identificational technologies with Bengali vegetables for the common people of this region.

1.4 RESEARCH QUESTION:

How do we collect information about different forms of vegetation?

What techniques would be most useful for feature extraction?

What algorithms should be used for classification to get the most accurate results?

Is it conceivable that this study would benefit people from all walks of life?

1.5 EXPECTED OUTCOME:

The researches anticipated outcome is the development of a system to digitize Bangladesh's vegetable classification system for future generations so that they can learn more about it. This type of technology will work together in a variety of different ways:

This system could aid superstore salespeople in categorizing various vegetables into various parts so that consumers can easily find what they're looking for.

This research can also be used in agriculture in a variety of ways. Plant acclimatization, farming, pest control facilities, storing and processing vegetables for sale, and so on [15]. It could have been beneficial to Bangladeshi farmers and the agricultural sector.

Land surveying, observing and documenting the total number of , and classifying them into subclasses will all benefit from this application.

In this study, a better dataset containing indigenous vegetables was given. This data could aid researchers in the development of an effective system in the future.

1.6 REPORT LAYOUT:

In **chapter 1**, this paper focuses on three major points. What we're doing, why we're doing it, and how we're going to do it. In general, the rationale for this study, as well as the expected outcomes, is addressed in depth in this chapter.

In **chapter 2,** this paper provides a comprehensive survey of relevant studies in this field. This section also includes a comparison of their works and essence. We consider the complexity of our project and how to interpret the problems in this section.

In **chapter 3,** this comment illustrates the approach used in this project. A variety of theoretical problems related to this study are also discussed. This chapter describes the data collection process, data preprocessing, feature extraction, and classification procedure.

In **chapter 4,** this chapter focuses on presenting the results of the previous section.

In **chapter 5,** a synopsis of this review. The final section of the report includes recommendations for future work, system implementation, and some shortcomings of our proposed process.

CHAPTER 2

2.1 RELATED WORK:

Femling, Olsson et al. [1] published a paper in 2018 describing a procedure for recognizing vegetables and fruits in a retail shop using recorded images and a system-attached video camera. The system's aim is to reduce the number of human-computer interactions, speed up the recognition process, and improve the GUI's usability in comparison to manual processes. A Raspberry Pi, an 800 by 480-pixel display screen, an 8-megapixel resolution camera, a processor to run the system, and a method of activation to represent the system's hardware size were used. They used an ImageNet dataset of 400 pictures per class derived from ImageNet, as well as 30 images per class for the camera used in this experiment. They used two CNN constructs for the classification: MobileNet and Inception, and evaluated accuracy and propagation time in two phases. The MobileNet top 3 testings yielded a 97 percent accuracy rate, which is very fast. Despite the fact that the top three precision levels are exceptional, MobileNet is still having trouble predicting kiwis and clementines. It can be improved by the number of images of the dataset. Retraining data sets from the real world might improve the reliability of the system. The heuristic evaluation pointed to a positive outcome for the developed process. Some features were missing from their framework, and users provided valuable feedback that enabled them to enhance the architecture. After three consecutive sessions, users reported no usability issues, but they wished for a larger display screen. They really would like to take more pictures of fruits and vegetables for future research so that they might split the classes into subclasses.

In 2013, Dubey et al [2] developed a method for categorizing vegetables and fruits that takes images of the vegetables and fruits as input and produces species and diversity as output. They used a dataset containing 2615 pictures of fifteen different types of vegetables and fruits from a supermarket. Picture segmentation, feature extraction, and training and classification are the three stages of the system's operation.

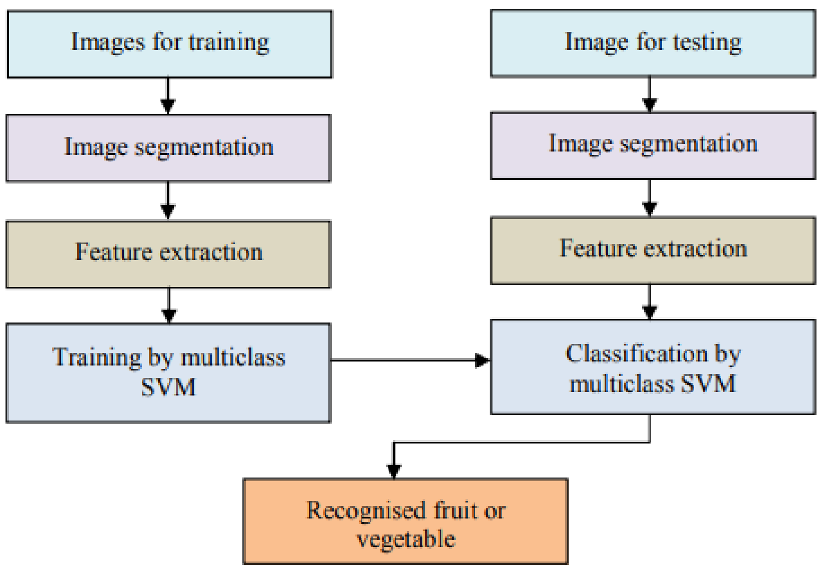

Fig. 2.1: Fruit and vegetable detection system flow diagram [2]

Image segmentation is done by using the K-means clustering process, and the ISADH component for each color image channel is measured and merged to produce a special histogram in this preferred system. They used MCSVM for both preparation and classification. The effectiveness of ISADH for the support vector machine and the nearest neighbor classifier was also measured in this paper, and the support vector machine was discovered to be the superior option for training and classification. They observed that the HSV color space is equivalent to the RGB color space after conducting the experiment. They experimented at five features in order to improve the precision. With forty pictures per class, the machine achieved an average accuracy of 93.62 percent in GCH, 95.27 percent in CCV, 95.82 percent in BIC, 96.96 percent in UNSER, and 98.90 percent in ISADH. They came to the conclusion that the suggested function is valid for the framework to understand vegetables and fruits, and that it produces more reliable results than other features.

Tippannavar et al. [3] published a technique for monitoring and classifying rare vegetable plants utilizing leaf texture exploration in 2017. They used 500 leaf images of six different types of vegetables for the analysis. MATLAB was used to test out the whole procedure. The median and trilateral filters were used to preprocess the files. Color and texture features have been extracted using Color correlograms and Fractal (SFTA) features, respectively, after the leaf portion was segregated from the context using the simplest threshold method and morphological operation. These characteristics were honed to aid in classification. k-NN and PNN are two types of classification for detecting vegetables and determining the unusualness of leaves. The k-nearest neighbor algorithm for vegetable identification had an accuracy of 86.39 percent and an unusualness of leaf of 75.04 percent, whereas the Probabilistic Neural Network algorithm had an accuracy of 75.70 percent and an unusualness of leaf of 71.24 percent. They may include diseases from different seasons and on different lands in the dataset for potential studies. They also want to improve the system by adding some high-level features, such as shape features (contourlet transforms, higher-order statistics, Zernike moments, etc.).

During the year 2020, Duth P et al [4] investigated a new method of vegetable intraclass detection algorithm that relied on deep learning rather than machine learning. The use of CNN (Convolution Neural Network) to identify different varieties of inter-class and interpersonal and inter vegetables minimized misclassification and correctly classified inter and intraclass vegetables. The dataset included 24 different types of vegetables, each with its own intraclass. In total, 3924 images were used, with 3210 images applied to train data and 714 images applied to test data. Pictures were first read and then resized and normalized for preprocessing before being used to train the data. They used Keras to implement the CNN model after completing the preprocessing.

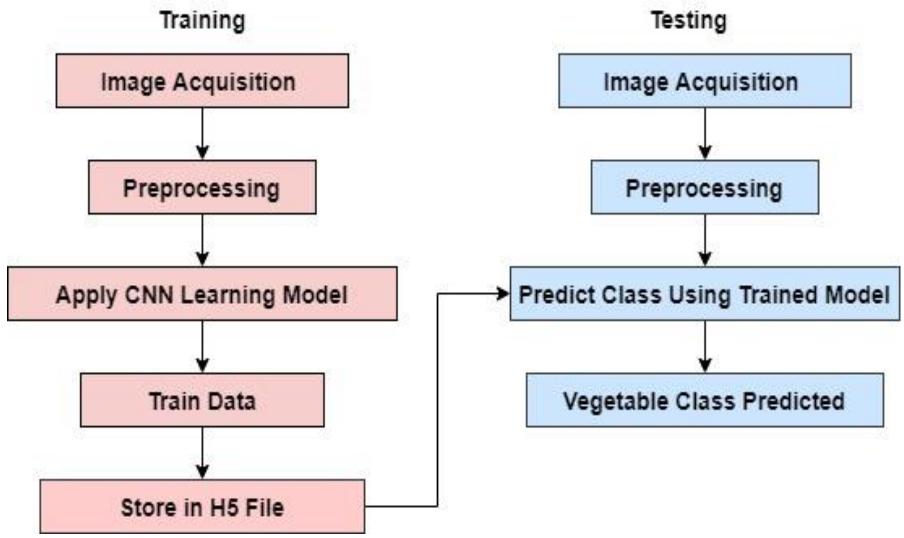

Fig. 2.2: Using CNN, a proposed approach for identifying vegetables has been proposed.[4]

The trained data was therefore saved in a hierarchical data format H5 file, which was later used to test the data for detecting the vegetable classification class. After a promising trial, they discovered that their proposed approach (CNN) had 95.50 percent accuracy, which was much better than the combined features and YOLO algorithm. They want to develop the system in the future by using more deep learning techniques like DNN and DBN, and they have a proposal to upgrade the recognition system by using cameras in stores and markets.

Bahia et al. [5] suggested a machine learning technique for identifying vegetables and fruits in 2019. They used the Dubey and Jalal (2015) dataset, which included 2615 images of a range of 15 different vegetables and fruits. The entire method was broken down into three steps: background removal, color along with texture, and finally classification. For the context subtraction, K-mean clustering was used. The color features have been extracted using both HSI and RGB color spaces. A total of nine color features were extracted: three with HSI and six with RGB. The coarseness, roughness, and smoothness of the image were determined by measuring the texture of an object's outer part. In this study, 7 textural features have been extracted: GLCM extracted 5 features, including correlation, energy, contrast, entropy, and homogeneity, and the other 2 features were extracted with the help of the other two techniques, LBP and HOG. They used the SVM method to train the dataset as well as to classify it. They also used KNN to compare their proposed classifier's results. After combining the different methods, they discovered that the SVM method had greater precision than the KNN method. With their proposed approach, they were able to achieve a 94.3 percent accuracy rate. They also demonstrated that this study generated significantly better results than previous methods. They want to deal with a single vegetable or fruit in a single photo because the dataset includes a variety of fruits and vegetables in a single image. They also intend to expand their dataset with more images of vegetables and fruits and apply deep learning techniques to it.

Sachin C, N Manasa et al. [6] identified a method for detecting and classifying three different green vegetables of various sizes in 2019. They used a dataset of 180 test images that included the settings of all three vegetables in combination. For the implementation of the method, which is known as a TensorFlow edition, they used the You Only Look Once algorithm and darknet. There, the cv2 Python Library from OpenCV was included. TensorFlow runs on both the CPU and the GPU. Since GPU is faster than CPU, they used it for their proposed algorithm. Initially, they manually deleted the outliers of the pictures from their dataset in order to complete the scheme. Then, in the training dataset, they drew boundary boxes around the vegetables. After that, they created an XML document for each image that included the bounding box dimensions as well as the vegetable groups. The XML documents were then loaded into the YOLO network as input and the trained weights were saved. The qualified weights and test dataset were then fed into the network. The boundary box dimensions and vegetable groups were predicted by the network. After that, they used OpenCV to draw the boundary box and display the class level. They then modified the YOLO configuration file to represent the number of classes the network had classified. More than half of the images and 70% of the videos were successfully categorized and graded using their model. Finally, they accomplished a precision of

61.6 percent with their analysis. They want to work with 3D pictures instead of 2D pictures for more enhancement, and they also want to investigate an autonomous harvest device.

Ahmad, Minallah et al. [7] developed a machine learning technique for classifying vegetables based on remote susceptibility in 2020. The aim of this research was to classify vegetables into different groups. The database they used in this framework was a free Copernicus platform database. It featured satellite images from around the world that were updated over time. They have used an app to gather data from field examinations. These ground truth data were used to determine the individual coordinates of the plants that were available in those areas. After processing the ground truth data, the raw image obtained from the Copernicus website was cut into a smaller picture that contained the concerned area. SNAP software was in charge of the whole stacking procedure. They utilized ENVI software to preprocess this method and used both unsupervised and supervised algorithms. To classify the vegetation operation, the SVM and ANN supervised learning algorithms were used, while the K-Means Clustering algorithm was used as an unsupervised learning algorithm. The system also classified non-vegetation artifacts. With ANN, this study achieved 92.46 percent precision, 90 percent precision with SVM, and 50.78 percent precision with K-Means Clustering. This research may be beneficial to a number of government-approved businesses and organizations. The information could be used to perform a variety of statistical analyses on crops and their location on a map. The locations found on the map may also be useful for potential urbanization.

Patil et al. [8] developed a model for edible herb classification using TensorFlow in 2018. This framework was investigated using an Inception-v3 based Tensor flow approach with OpenCV as the primary library database. They used an HP pavilion sixth generation computer with 8GB memory and a 64-bit Windows 10 operating system for the hardware. In this device, a Sony Xperia X-Plus smartphone with 4GB RAM was used as testing hardware. Tomatoes, cucumbers, carrots, and onions were among the edible herbs used to establish the dataset. This vegetable pictures classification system's method of construction was separated into four steps:

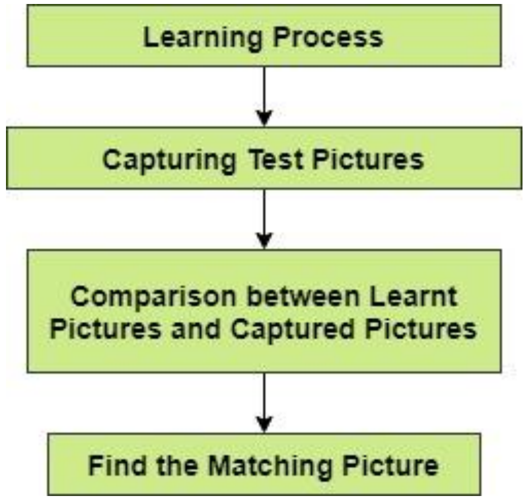

Fig. 2.3: Vegetable classification sequences. [8]

They preprocessed the images and named the data using a supervised learning CNN. The Inception-V3 model was then subjected to transfer learning. They kept the prior layer's parameter, extracted the last layer, and then retrenched the new final layer with the dataset. The final layer of the system was equipped using the Propagation Algorithm, and the weight parameter was modified using the Cross-entropy Cost Function. The precision of this identification method was found to be 99 percent, making it more dependable for users as a vegetable classification system.

Rocha, Hauagge, et al. [9] developed an automatic vegetable and fruit categorization system based on pictures in 2010. In a multi-class sense, they looked at statistical color-texture features as well as functional appearance descriptive terms for categorizing vegetables and fruits. They also tested several state-of-the-art Computer Vision features in a variety of formats and arranged the framework with reasonable precision using cross-validation based procedures, resulting in the integration of the best classifiers and features into a single unified process. They assembled images from a local distribution center of fruits and vegetables for five months to develop the dataset, which they dubbed "supermarket generated data collection." They photographed their dataset with a Canon Powershot-P1 camera. Their dataset consisted of 2633 images classified into fifteen different groups. They utilized LDA, SVM, K-NN, and classification tree classifiers, as well as BIC, GCH, CCV, and Unser features, to classify the system. In their report, they did not mention the accuracy rate, but they did show that their suggested approach could reduce the error rate by up to 15% when compared to the baseline.

Seng et al [10] discovered a procedure for identifying fruits in 2009. To improve detection accuracy, their presented scheme used three techniques for analysis. These are characteristics based on color, form, and scale. For the experiment's training and research purposes, 50 images of fruits were taken. They had qualified 36 photographs and used the remaining 14 for research. To identify and classify the fruits, the system used the K-Nearest Neighbor algorithm. To perform the classification process, they followed a set of steps. They began by selecting the fruit image and then cutting off the fruit's area. They then determined the average value for RGB color components, reduced noise, ordered geometrical values, and performed morphological operations. They used these KNN in the system to classify the image and determine the output. They had achieved an accuracy of 90% using that same Fruit detection method. This research would be very useful in a variety of fields, including image retrieval, education, and environmental science.

In 2019, Nosseir et al [11] developed an automated classification system for several fruit species including the detection of putrid fruits using SVM and KNN algorithms. The algorithms they used in this experiment to evaluate the color and texture of fruit images. For their experiment, they used four different types of fruits: Mango, Strawberry, Banana and Apple were all from Shutter-Stock, COFI-Lab, I- Stock, and other sources. While preprocessing the photos, they first converted them to grayscale, then increased contrast to reduce noise and improve picture quality. The median filtering method was also used to remove noise. Color and texture features were extracted using FFT and GCLM. The system was categorized using a non-parametric method known as k-nearest neighbor. To obtain an accurate result, six types of KNN classifiers were used: weighted KNN, medium KNN, cubic KNN, cosine KNN, fine KNN, and coarse KNN, and the training outcome was 95 percent, 93.8 percent, 90 percent, 83.8 percent, 96.3 percent, and 25 percent, respectively. 46 images of those four types of fruits were taken for testing and received 100 percent accurate results. Following that, they examined both fresh and putrid fruits in order to distinguish them. They extracted texture and color features before employing quadratic SVM and linear SVM algorithms. The accuracy of the quadratic SVM was higher than that of the linear SVM. The result for quadratic was 98 percent accurate, and the result for linear was 96 percent accurate.

In 2019, PL. Chithra et al [12] developed a model to classify fruits using image processing methods. They used 140 images for training and 50 for testing, with the training dataset supposed to contain 70 banana and 70 apple photos and the testing dataset containing 25 banana and 25 apple photos. For this fruit detection system, MATLAB was used to execute the algorithms, and Support Vector Machine (SVM) was used as a classifier.

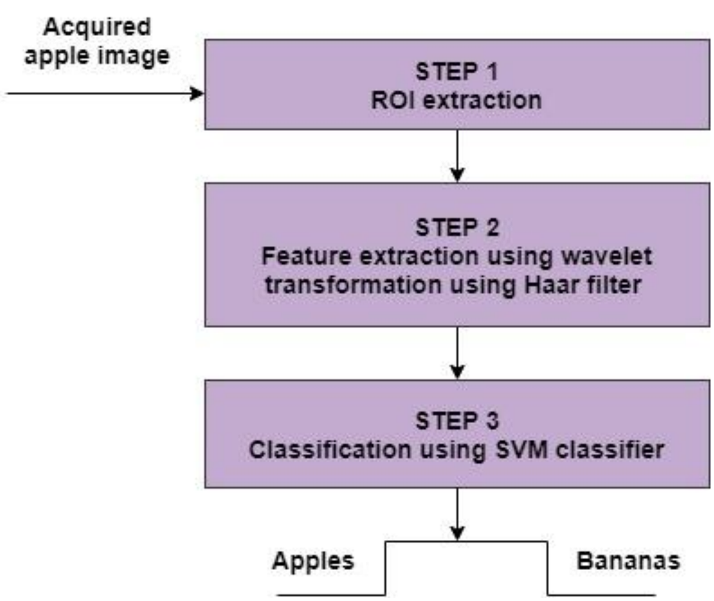

Fig. 2.4 Illustration of the proposed system. [12]

Some steps were taken as a result of the method's execution. Initially, they loaded the RGB images and converted them to HSI. They then took the Hue component image and subtracted the background from it. Following that, they used OTSU's method for reaching the threshold and extracting ROI to fill in the gaps. The ROI-based image was then loaded. They then extracted the features using Haar filters and wavelet transformation. They then used SVM to classify images of bananas and apples. When the experiment results were compared to KNN, they discovered that SVM delivered 100% precision.

Vegetation detection can be useful in a variety of ways. It can sometimes help government organizations gather information about various vegetable plants and their classes. They can use the data for various types of surveys as well as reports on various plants or herbs. The vegetables will be seen in a new light by the new generation in the world. People will be introduced to different groups of the same edible herb by botanic classification of various vegetables. Agriculture in Bangladesh would also benefit from this application. It will be extremely useful for increasing new vegetable categories, grouping them for storage, and selling them at markets. The digitalized method of detecting vegetables has the potential to boost the country's economy. Supermarkets can benefit from this system. Customers as well as shopkeepers would profit from this. Clearly, this program will assist the general public in quickly recognizing vegetation.

2.2 CHALLENGES:

1. **Dataset:** Most challenging part of any research work is creating the dataset. Mainly it was harder for us to make a dataset of vegetables in Bangladesh because there were no previous organized dataset collection techniques. Even from different places we

collected data which really gave us trouble. As different places have different types of vegetables, that's why we had to collect them from different places.

2. **Cleaning Noise:** One of the most important preprocessing parts is cleaning up the images from unnecessary noises. As vegetables were outdoors and indoors both we had different types of noises in indoor images had shadow or more unnecessary portions in the frame on the other hand outdoor images had light issues because it was depending on the weather, when it was sunny it was over exposed sometimes even in gloomy time there was lack of lights.

3. **Multiclass Issue:** We mainly collected all the images of vegetables from real vegetables and from real places. As the same vegetable has different shapes and sizes it was really difficult to collect all of them and for lack of variety initially our model started predicting wrongly. To avoid this, we had spent lots of time to find out the same kind of vegetable’s different shapes and sizes.

4. **Model:** There was lots of different research related to our work but the main difference is the region of vegetables as almost all the works done in outside of Bangladesh and there are some significant differences between Bangladeshi and other countries vegetables, we are confused about selecting models to classify them. Then we select a model which will be really helpful to feature extraction from image for the get more details about object.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTDODUCTION

It is important to choose an effective and optimal methodology for this project. So that we can process our data accurately and train the machine from this limited dataset. Here we choose some sort of methodology and algorithm workflow we used in this project which give us a good result in the output. In this chapter describe our object of research, algorithm which we used and our data with some analysis with proposed workflow.

3.2 RESEARCH SUBJECT AND INSTRUMENTATION

Way of data collection for this research work and the tools and algorithms we have used to make this work easier will explain them.

Vegetables we have used for this work were:

- Cauliflower
- Carrots
- Tomato

Around 800 vegetables have been collected for this work which were mixer of above three type of vegetables. We have collected these vegetables image from our region. We store all of the images with classified by their categories

The structure of our dataset pipeline explains in figure 3.1

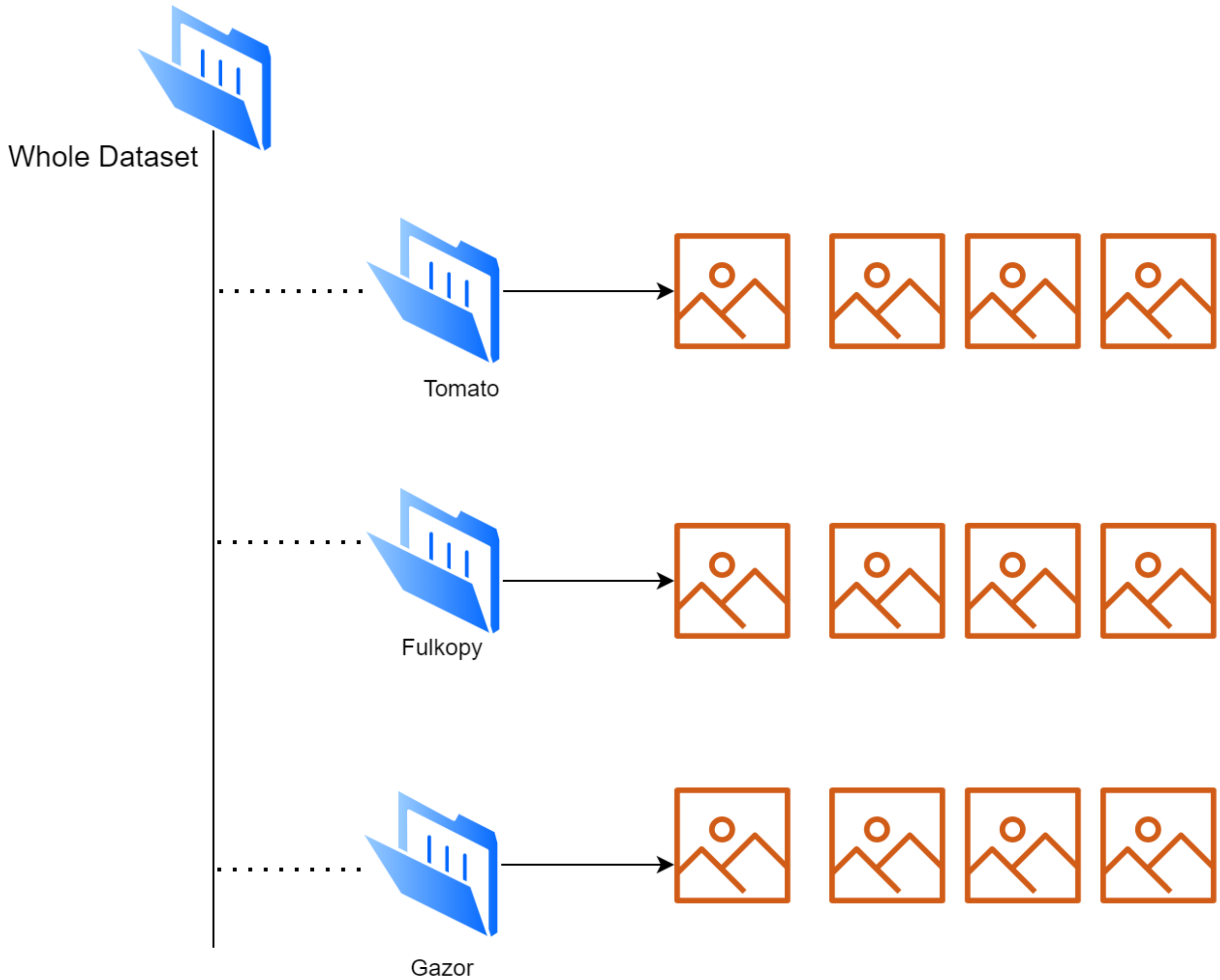

Figure 3.1: The dataset pipeline

Reading the dataset for feature extraction is the most important thing to start the work. And figure 3.2 is describing how our algorithm read our dataset from different folders and extract the arrays from them.

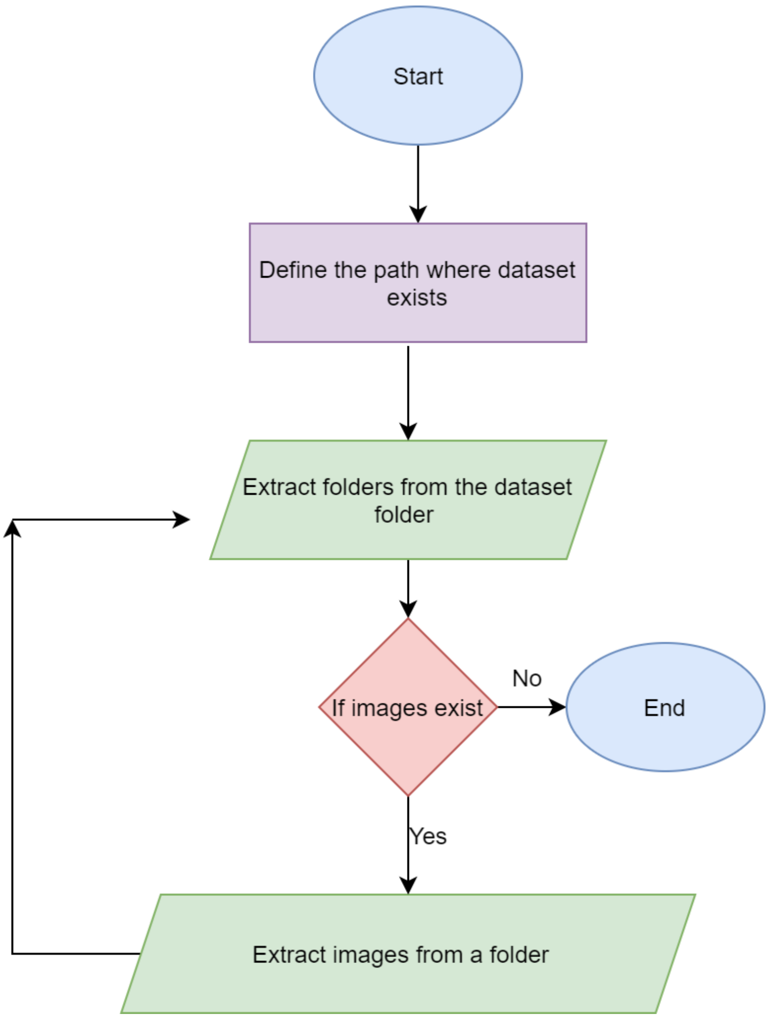

Figure 3.2: Accessing the data.

This is a flow chart of how we access our dataset. At first we defined the dataset path which is our local or remote storage path. After that we extract folders from the dataset folder with is categorized by the categories and check for the image resource is exist or not. When got the image from the resource then extract image from these folder for further process and repeat this process for all image and there categories to complete image extraction process.

3.3 DATASET UTILIZATION

Images of raw vegetable collection is the toughest part of this work. Gathered almost 800 images of three different types. The collection happened mainly from different vegetable gardens of Bangladesh. The main model building starts with converting the images into numbers and then we apply convolutional neural network for applying random feature extraction matrixes on them for better classification.

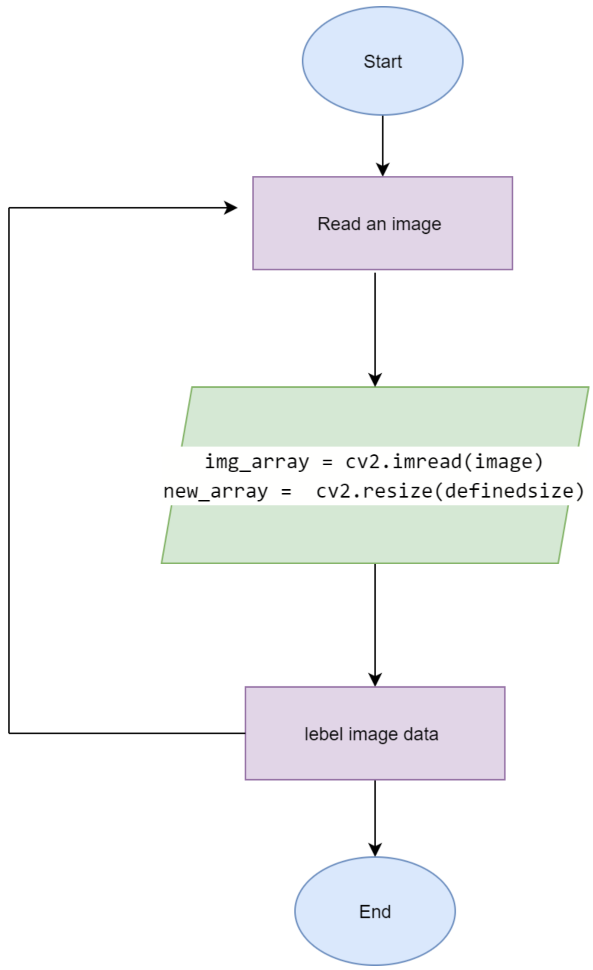

Figure 3.3: Converting images into numbers

In this figure 3.3 presenting the flow chart of converting the image in number. Here firstly read an image and converting the images as image array means converting image into number and then resize the array of this image. From the image array we level that image using the image data and continue the procedure for another image.

3.4 STATISTICAL ANALYSIS

The variety in our dataset will be explained in this part.

Table 3.1: Distribution of dataset

Name of vegetable	Number of vegetables	Single vegetable image	Multiple vegetable in an image
Cauliflower	292	83%	17%
Carrots	211	77%	23%
Tomato	315	71%	29%

In this table we shown the information about our dataset. Here 292 Cauliflower image used where 83% of single vegetable image and rest of 17% is multiple vegetable image in an image. About 211 Carrots image used where 77% is single vegetable image and rest of 23% is multiple vegetable image and total 315 image used for Tomatoes. Where 71 % of these are single vegetable and rest of 29% are multiple vegetable image in an image.

Two different types of data have been collected:

- Individual vegetables
- Bucket of vegetables

The verity of dataset is explained in figure 3.4 pie chart

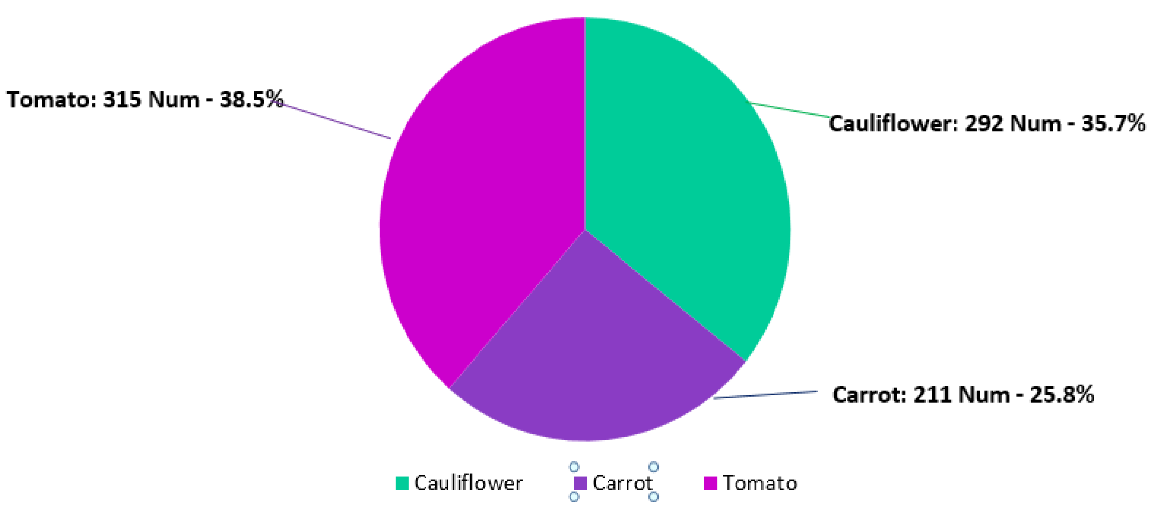

Figure 3.4: Verity of dataset

3.5 PROPOSED METHODOLOGY

To find out a perfect solution we followed a workflow in figure 3.5 we tried to visualize the workflow.

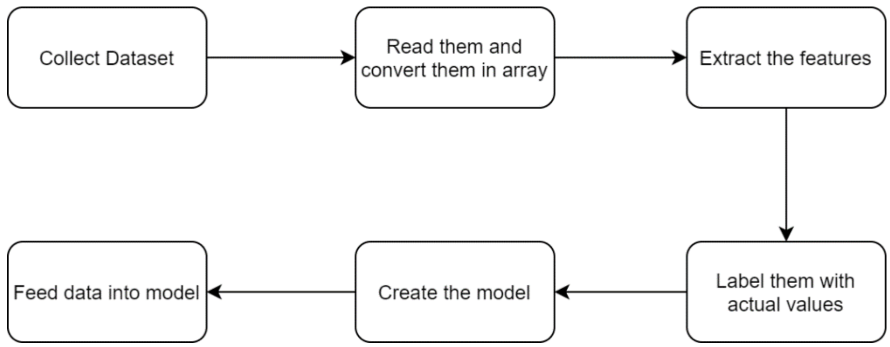

Figure 3.5: Proposed Workflow

According to the above figure we collected the row data of vegetables that mean the images of the vegetable but we know machines can work with only numbers that's why we converted those images into grayscale and after that convert into array of numbers. And after that we classify them according to vegetables' names as we used supervised learning. We had to label them all. And in the last stage we created the model and trained the model to predict from unseen data.

We used supervised learning algorithm which will help to classify new unseen data from our supervised model which are trained by our dataset. We used Convolutional neural network (CNN) as our supervised learning algorithm. CNN is used to getting the more accurate result as this algorithm helps to extract data from image with more object detection. For feature extraction from image CNN is well known algorithm and we used this algorithm in our model to build a perfect learning approach for machine so the accuracy rate will increase by training more image.

3.6 IMPLEMENTATION REQUIREMENTS

Python 3.8:

Python is a high-level programming language [16]. Recently it has been vastly used for Data Science and AI implementation and beside that we can use it for web and mobile application development. The easy structure and syntax give it acceptance to all types of developers. These advantages actually poke us to use this language for our work. And obviously its huge community supports always backing the developers.

Anaconda 4.5.12:

This the free and open-source dispersion of python [17]. This is likewise accessible for R programming language. This is really a pack installer. By introducing anything it introduces heaps of vital instruments for information science. Indeed, it even accompanies an idea of a virtual climate. We can detach various tasks from one another with the goal that we can utilize various necessities for every one of them. We utilized the 4.5.12 variant of boa constrictor, the refreshed form of the time.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 INTRODUCTION

After processing our data for machine understanding and used this data for train the machine using AI model and Convolutional Neural Network (CNN) we get the result of our processing effort in this project. In this chapter we describe our AI model with some statistical analysis and graph of train accuracy, train loss, validation accuracy, validation loss and below shown our result analysis with confusion matrix.

4.2 EXPERIMENTAL SETUP

In the past segment, we completed our data arrangement, preprocessing, incorporated extraction and set a way to deal with show up at the target. According to the system now we need to apply CNN shows better results so we will analyze these three techniques in this part. We endeavored on the subjective forest area in our dataset. We used 80% of the data for getting a ready explanation and 20% for testing the model.

Beneath figure will depict the rundown of the model.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 98, 98, 32)        320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 49, 49, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 47, 47, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 23, 23, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 33856)             0
_________________________________________________________________
dense (Dense)                (None, 3)                 101571
=================================================================
Total params: 120,387
Trainable params: 120,387
Non-trainable params: 0
_________________________________________________________________
```

Figure 4.1: Summary of the model

The above model is a sequential model. This sequential model means it works maintaining the sequence, it process data one after another. This figure shows the summery of this models and it result. Convolution Neural Network algorithm are used in this model. Here we used picture means 2D image that's why it works with Conv2D and we use max_pooling for this 2D images. Here Dense for repeating the process to get more accurate value as it work with some random value from our image arrays. So we use Dense multiple time, we set the value Dense 15 and get more accurate value in our graph.

And below figures (4.2, 4.3, 4.4 4.5) will show us the training accuracy, train loss, validation accuracy, validation loss of the model according to epochs. We used 15 epochs for this model.

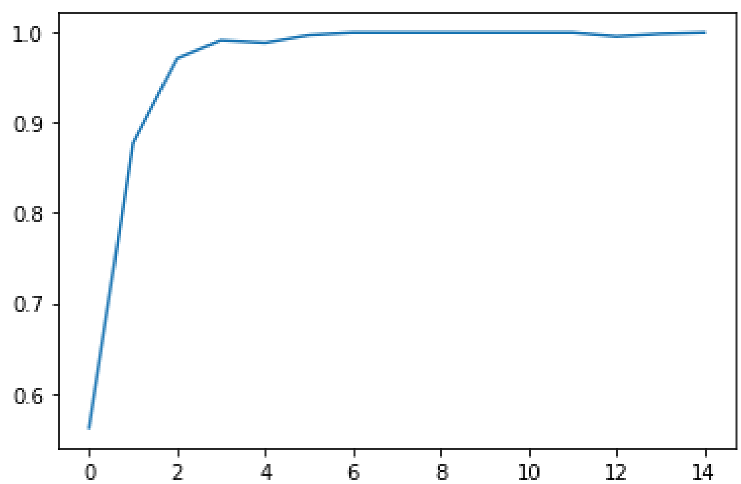

Figure 4.2: Train accuracy

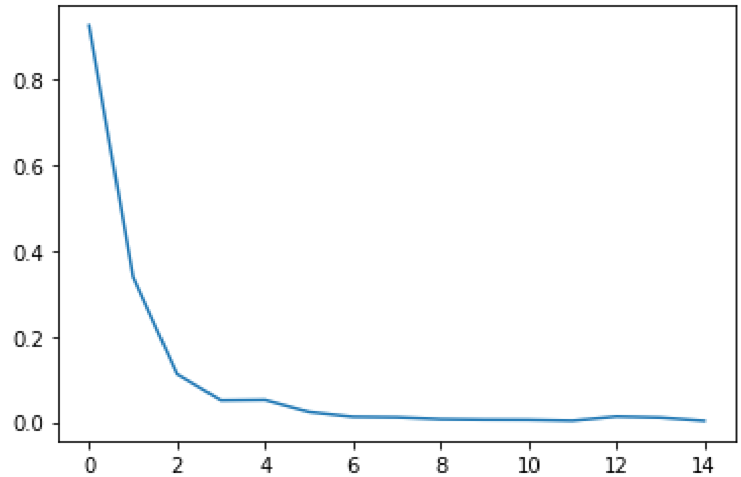

Figure 4.3: Train Loss

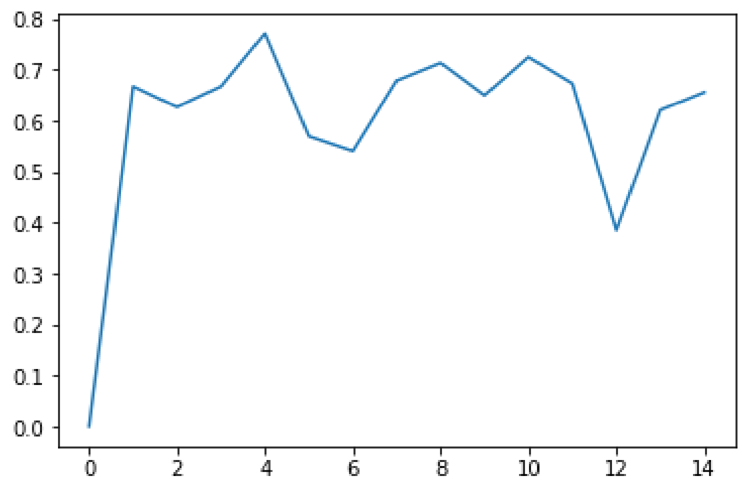

Figure 4.4: Validation Accuracy

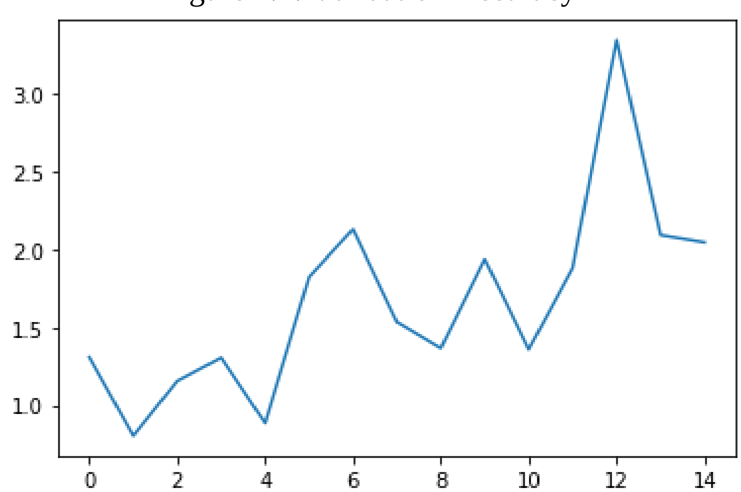

Figure 4.5: Validation Loss

So from above figures we got train accuracy 95.50% and validation accuracy near 70%. We got these graph by plot our training history. As our algorithm and model work with random values from our provided arrays, it will shows different values for multiple epoch and execution.

4.3 EXPERIMENTAL RESULTS & ANALYSIS

The confusion matrix of validation has been given below

	Class 1	Class 2	Class 3	Classification overall	Producer Accuracy (Precision)
Class 1	38	7	12	57	66.667%
Class 2	5	28	6	39	71.795%
Class 3	7	15	32	54	59.259%
Truth overall	50	50	50	150	
User Accuracy (Recall)	76%	56%	64%		

Figure 4.6: Confusion matrix.

This is the confusion matrix we got. We got producer accuracy 66%, 71%, and 59% respectively and user accuracy 76%, 56% and 64% respectively for our 3 classes of data cauliflower, carrot and tomato. This level of accuracy will be increase by updating our dataset size. Here our train accuracy and validation accuracy we about 95.50% and 70% respectively.

CHAPTER 5

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

5.1 SUMMARY OF THE STUDY

This exploration venture's primary objective is to perceive vegetables. To digitize the current world we need to offer comprehension to the machines. We removed the pictures cluster with the assistance of open-CV and utilized convolutional neural networks for extricating the highlights and preparing the model. Also, after all we got 100% preparing exactness and 65% approval precision for approval we utilized 20% of our dataset.

In this study our intention was to learn and implement technology for minimize the effort of human and automation to solve related to our regional problem. That's why we choose our core field as agriculture and focus on vegetable classification. We used some advanced technology Artificial Intelligence and Machine Learning to work with this. We study a lot to this field work which previously done for other region. We collect data from our local garden and apply CNN algorithm to our dataset and we got some good accuracy result after building model for train data.

5.2 CONCLUSION

We studied the feature extraction for our regional vegetables using the Convolutional Neural Network (CNN). Using this classification architecture we got the accuracy of almost 95.5%. Using this CNN algorithm the feature extraction for our collected image was the most reliable architecture for this work. We show here some statistical diagram about train accuracy, train loss, validation accuracy and validation loss. Our study will be the reliable explanation for vegetable classification and feature extraction using machine learning algorithm. Vegetables are the main food in our feasting. In the event that we can perceive the vegetables in future we may additionally explore it. Each individual needs to go to a super shop to purchase vegetables. In the event that we can make a framework where vegetables are recognized and considered different items we may decrease the exercise in futility. So we are in the process now we are 65% precise and in future we need to build it. With increasing the data size we will make it more standard and more reliable and this study intended us to make a stable framework for all device and also for industrial level to recognize our regional vegetable to make computer more reliable and minimize the manual human effort.

5.3 IMPLICATION FOR FURTHER STUDY

We have a lot of plan about the better version of this project. As it will be very helpful for region in many ways like government project, agricultural sector, vegetable processing industries, students and also general people to classify the vegetable and learning about them. So we will try to improve this project to cover all of needs as they need related to our study and project. So here we have some plan for future work with this project.

- Increase the dataset as we want to show more reliable data output.
- Increase the category to cover all the most useful vegetables.
- Work with the improvement of the accuracy
- Detecting the vitamins and calories with the vegetables.
- Implementing APIs for all platform for better usability.
- Develop mobile application for general user.

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