PLANT SPECIES CLASSIFICATION USING NEURAL NETWORK

BY

ASIQUR RAHMAN ANIK
ID: 191-15-12337

AND

MD. FAZLE RABBI
ID: 191-15-12740

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

Supervised By

Syeda Tasnim Alvi
Lecturer
Department of Computer Science and Engineering
Faculty of Science and Information Technology
Daffodil International University

Co-Supervised By

Dewan Mamun Reza
Lecturer (Senior Scale)
Department of Computer Science and Engineering
Faculty of Science and Information Technology
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project/internship titled **"Plant Species Classification Using Neural Network"**, submitted byAsiqur Rahman Anik, ID: 191-15-12337 and MD. Fazle Rabbi, ID: 191-15-12740 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment 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 *29 January, 2023*.

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Jahangirnagar University

DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Syeda Tasnim Alvi, 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.

Supervised by:

Syeda Tasnim Alvi
Lecturer
Department of CSE
Daffodil International University

Co-Supervised by:

Dewan Mamun Reza
Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Submitted by:

Asiqur Rahman Anik
ID: -191-15-12337
Department of CSE
Daffodil International University

Rabbi

MD. Fazle Rabbi
ID: -191-15-12740
Department of CSE
Daffodil International University

ABSTRACT

The task that is done in our project is to classify and identify the species of different plant using neural network. The work is done mainly for removing the problems that arises when classifying different types of plants in their own category. In this research paper, we propose the use of neural networks for plant species classification. Our approach involves the collection and labeling of a large dataset of plant images, which are then used to train and evaluate the performance of neural network model. The neural network model was trained on a variety of plant images, including leaves and fruits to ensure a diverse and representative dataset. To improve the accuracy of our classification, we also employed data augmentation techniques, such as rotation and scaling, to artificially expand our dataset. Our results show that neural network models can accurately classify plant species, with a top accuracy of 90.2%. Additionally, we found that using a combination of different image types, such as leaves and flowers, improved the classification performance compared to using a single type of image. Overall, our study demonstrates the potential of neural networks for plant species classification and highlights the importance of a diverse and representative dataset for achieving high accuracy. This research has practical applications in fields such as agriculture, where accurate plant species identification is necessary for crop management and yield optimization.

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CHAPTER 1
Introduction

1.1 Introduction

Plant species classification is a fundamental task in botany that involves the identification and grouping of different plant species based on their characteristics. This process is essential for understanding the relationships between different plant species and their various attributes, including their physical appearance, growth habits, and ecological roles. In the past, plant species classification has been performed primarily through morphological analysis, which involves examining and comparing the physical characteristics of different plant species. However, this method can be subjective and time-consuming, leading researchers to seek out alternative approaches. One promising solution is the use of neural networks, which are the types of artificial intelligence that can be trained to recognize patterns and classify objects. Neural networks have the ability to learn and improve their accuracy over time, making them a powerful tool for plant species classification. By analyzing large amounts of data and classifying plants based on a variety of characteristics, neural networks can provide a more comprehensive and objective approach to plant species classification. We will discuss the benefits of using neural networks, including their ability to handle large amounts of data, classify plants based on a variety of characteristics, and provide objective results. We will also examine the limitations and challenges of using neural networks for plant species classification, and discuss future directions for research in this area.

The method utilizes unique features of plants such as leaf shape and texture for accurate classification. As CNN are used to extract unique feature which we will be using on this paper therefore it will be a great challenge for us to get the right features for the specific plant.

1.2 Motivation

The classification of plant species is a crucial task in the field of botany, as it allows for a better understanding of the relationships between different plant species and their various characteristics. However, traditional methods of classification, such as morphological analysis, can be time-consuming and subjective. This is where neural networks come in. Neural networks are a type of artificial intelligence that can be trained to recognize patterns and classify objects.

They have the

ability to learn and improve their accuracy over time, making them a powerful tool for plant species classification. One of the main benefits of using neural networks for plant species classification is their ability to handle large amounts of data. In traditional methods of classification, data must be manually analyzed and inputted by researchers, which can be a tedious and time-consuming process. With neural networks, this process is automated, allowing for faster and more accurate classification. Another advantage of using neural networks is their ability to classify plants based on a variety of characteristics, such as leaf shape, flower color, and growth habits. This allows for a more comprehensive and accurate classification, as traditional methods often rely on a limited number of characteristics. In addition, neural networks can classify plant species in a more objective manner, reducing the subjectivity that can often occur in traditional methods. This is especially important in cases where multiple researchers are involved in the classification process, as individual bias can influence the results. Overall, the use of neural networks for plant species classification offers numerous benefits, including speed, accuracy, and objectivity. By implementing this technology, researchers can more efficiently and accurately classify plant species, leading to a better understanding of the relationships between different plant species and their characteristics.

Objective of our research :

The future of image processing work is beyond our expectation and helpful in the field of every technological sector. Some reasons are pointed below :

- To contribute in the field of botany and zoology. As these two sectors need many features of both plants and animals for their research and gathering knowledge.
- To get the highest possible accuracy rate. We are to classify image recognition more precisely than before and more detailed work will be introduced to showcase in recognition feature.
- As said earlier image processing has more wider field to explore therefore different types of neural network architecture will be used together in the near future for better understanding.
- To distinguish plants types and recognizing the right one as many time we fail to recognize the preferred one we wanted

- To contribute in the medical sector for recognizing skin type diseases that will be a thing to worry about in the near future.

1.3 Rationale of the study

The classification of plant species is a vital aspect of botany, as it allows for a better understanding of the relationships between different plant species and their characteristics. However, traditional methods of classification, such as morphological analysis, can be time-consuming and subjective. This is where neural networks come in. Neural networks are a type of artificial intelligence that can be trained to recognize patterns and classify objects. They have the ability to learn and improve their accuracy over time, making them a powerful tool for plant species classification. The use of neural networks for plant species classification offers numerous benefits, including speed, accuracy, and objectivity. With traditional methods, data must be manually analyzed and inputted by researchers, which can be a tedious and time-consuming process. With neural networks, this process is automated, allowing for faster and more accurate classification. In addition, neural networks can classify plant species based on a variety of characteristics, such as leaf shape, flower color, and growth habits. This allows for a more comprehensive and accurate classification, as traditional methods often rely on a limited number of characteristics. The objective of this study is

to evaluate the effectiveness of using neural networks for plant species classification. To do this, we will compare the results obtained using neural networks to those obtained using traditional methods. This will allow us to

1.4 Research Questions

We faced many difficulties while doing the research as we had to collect enough data for our paper so that the program can identify specifically the plants we want to recognize. The following questions arises when this work is being done.

- Is it possible to reduce social and racial biases from the dataset ?
- Is it possible to work with only limited images ?
- Is is possible to improve plant species classification system using this approach ?
- Can the learning process be used to pre process the data ?

1.5 Expected Outcome

The paper "Plant Species Classification using Neural Network" is to determine the effectiveness of using neural networks for plant species classification. In order to do this, we will compare the results obtained using neural networks to those obtained using traditional methods. It is expected that the use of neural networks will result in more accurate and efficient classification compared to traditional methods. This is due to the ability of neural networks to handle large amounts of data and classify plants based on a variety of characteristics, as well as their ability to learn and improve their accuracy over time. Additionally, it is expected that the use of neural networks will result in a more objective classification process, reducing the subjectivity that can often occur in traditional methods. This is especially important in cases where multiple researchers are involved in the classification process, as individual bias can influence the results. Overall, the paper is carried out to demonstrate the effectiveness of using neural networks for plant species classification and to determine if they offer any significant advantages over traditional methods.

1.6 Project Management andFinance

We are a group of 2 member doing this work. We had collect our dataset from some browsers and then we needed to compare the dataset and select the best ones. After selecting we had to train some data and ensuring the pixels that are required to finish the work. We didn’t need to put that amount of money for something because that is given in this research paper is knowledge and time. Therefore we just needed to be accurate and disciplined when doing this work.

The following illustrates the project flow:

I. Searched extensively for studies related to our project.

II. Selected research studies that were relevant to our area of study.

III. Analyzed all of the research papers that were chosen to find out more about plant species with deep learning.

IV. Extracted specified datasets from the database of plants images.

V. Prepared and processed the dataset to enable deep learning algorithms to classify it.

VI. We put the best deep learning classifiers into practice to accomplish our goals.

VII. Trained and put to the test the classifiers to show the accuracy of our work.

VIII. Presented the completed research project report in written form.

1.7 Layout of theReport

Chapter 1 mainly focuses on the introduction, motivation, rationale of the study and also the report layout.

Chapter 2 discusses what has already been done in this sector. The scope resulting from their field's constraint is then demonstrated in the second chapter's final portion.

Chapter 3 highlights the theoretical debate surrounding this study's finding. From this chapter we know about the techniques and models that are used to evaluate our work. Therefore, this chapter will be elaborated for CNN's procedure methodologies. To evaluate accuracy of the generated captions, the detailed information of evaluation matrices and other approaches are elaborated.

Chapter 4 includes experimental results, performance evaluation, and explanation of the end results. This chapter contains several experimental images which will be discussed further more.

Chapter 5 discusses about the impact of this work which will provide something for the society, environment and sustainability plan.

Chapter 6 guides us to the conclusion of our work. Also it demonstrates about the future scope on this field.

Chapter 2
Background Study

2.1 Preliminaries and Terminologies

We will talk about similar works, a research summary, and some of the research's challenges in this part. Many papers with their works will be discused . We will present works related in the research summary section. We will also talk about the accuracy and loss level in the challenges section. We will know more about the collection of datasets. We will compare the works of others and make sure to mention the advantages that we will get from this paper. We will rather be simplified fraom the complexity that will arise soon when we start discussing about everything.

2.2 Related Works

Many papers have been published for plant species classification using neural networks. Many complicated systems comprising of rudimentary visual object identifiers and language models were utilized in the early years of image classification research [1]. These systems were primarily rule-based, hand-designed and not flexible at all . Furthermore, these technologies only worked on a limited set of images. [2] handled image classification as a machine translation task. However, this method was unable to capture the image's fine-grained interaction between the components. The method CNN is used in our work as we want to be precise in finding and identifying our images that is given in the task. As we can in this [3] research paper many techniques is used and explained to classify plants using different models.

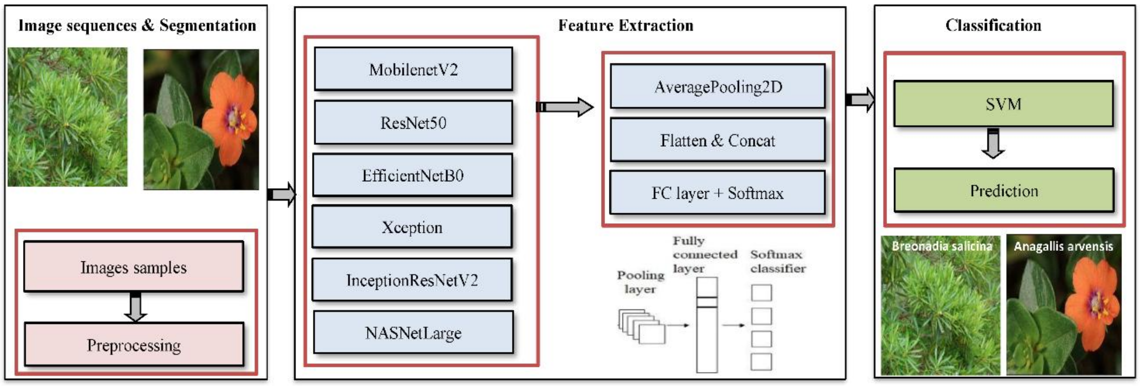

Fig 2.1 Workflow of Image Classification

As we can see here many models are used and the feature extraction is shown. We have taken 100 images for each plant for our experiment and as we said we used the (mobile net) model of many models since we found it preferable to use. As we move on to next [4] paper we can see that they used (Alex net) model here which is different from the previous model as we discussed and it found an accuracy of about 99%. Because of it's rising demands for image classification it was certain to come this accurate. But the model we used is sensible and less time consuming in identifying images. Then we find in [5] that ANN model is used which is Artificial Neural Network. It is another model and said to be an unsupervised learning. We prefer CNN because of the following things:

- Weight Sharing
- Memory Saving
- Equivariance
- Independent of transformation

Therefore, these are the related works that we mentioned and discussed and as we move on we will learn more about the things.

2.3 Comparative Analysis andSummary

There are many models that can be used for plant species classification. In our research we used CNN model for classification because we can get our required accuracy from CNN model. The table for differentiation of different models are given below.

Serial No.	Types of Neural Network	Accuracy
1.	Convolutional Neural Network (CNN)	97.81 %
2.	Artificial Neural Network (ANN)	92.78 %
3.	Recurrent Neural Network (RNN)	96.87 %
4.	Restricted Boltzmann Machine (RBM)	94.62 %

As we can see we can get the highest possible accuracy through using Convolutional Neural Network and we will be using it for any kind of species classification.

2.4 Scope of theProblem

Accurate plant species classification is important for a number of applications, including conservation, ecology, and agriculture. However, traditional methods for plant species classification, such as manual inspection and morphological analysis, can be time-consuming and subjective. Recently, interest is grown in using ML techniques for plant species classification. CNNs, in particular, have shown promise due to their ability to learn hierarchical features from images. However, there is a lack of research on the effectiveness of CNNs for plant species classification, and it is not clear how well these models generalize to different plant species and datasets. By addressing this problem, the authors hope to provide a more reliable and efficient approach for plant species classification and to contribute to the broader field of machine learning for plant science. CNN has many advantages rather than disadvantages therefore we prefer to use this model in the near future for any kind of work as it will be beneficial for us.

2.5 Challenges

There are many challenges that needed to be faced. One challenge is related to data collection and preprocessing. Plant species classification using CNNs requires a large and diverse dataset of images of plant leaves, which can be difficult to obtain. We had to pre-process our data for using CNN model. The images may also need to be preprocessed to ensure that they are of consistent size and quality. Another challenge is related to defining and training the CNN model. Plant species classification is a complex task, and it may be difficult to design a CNN model that is able to accurately classify different plant species. The authors may need to experiment with different network architectures and training parameters to find a model that performs well on the task. A third challenge is related to evaluating the performance of the CNN model. It is important to use a robust evaluation method to ensure that the model is able to generalize to new, unseen data. The authors may also need to consider the trade-off between accuracy and computational cost when evaluating the model. Finally, the authors may face challenges in terms of generalizability. Further it is needed to evaluate the generalizability of the model. Overall, the research paper "Plant Species Classification using Convolutional Neural Networks" is likely to face a number of challenges related to data collection, model design and training, evaluation, and generalizability.

Chapter 3
Research Methodology

3.1 Introduction

In this part we will discuss about the about our research function. How it has been done and what are changes that we will bring to this project.

3.2 Research Subject andInstrumentation

The subject of this research as we known from earlier is that plant species classification system using the neural network. We worked in python as it is a machine learning research project. We have done and run our program in google colab. We took help from many libraries during our work and we took our datasets from various sources. We are to collect more data in the near future as we want to work on it in the near future. Also we want to make this as an application for everyone to know about different species. There are thousand of species except plants and some are rare species that we know only little about. By this system we will not be able to classify them but also identify its characteristics and differentiate between many species. AI is the future and we probably are in the track that sooner or later people would love to work on.

3.3 Workflow

The paper contains few stages of workflow which are derived below :
Stage 1 – Dataset Modification: We collected dataset from public domain and used accordingly.

Stage 2 - There were some data with noise and inaccuracies in this updated dataset. First we process the data manually and the next steps are done.

Stage 3 - Data Pre-processing: We had to go through data pre-processing and resizing for training purposes. To achieve better results, we scaled the photographs to the same proportions or sizes along with some other works.

Stage 4 - Model Implementation: We trained our dataset on several models so that we can evaluate which model and setup provides us the best result for this particular dataset.

Stage 5 – Cross validation: It is implemented after the CNN model is ensured and it starts working.

Stage 6 - Performance Evaluation: The results are mentioned along with the appropriate tables and graphs. Following the training and testing of those processes.

Stage 7 – Conclusion: Conclusion will be mentioned emphasizing the needs of further study in this field.

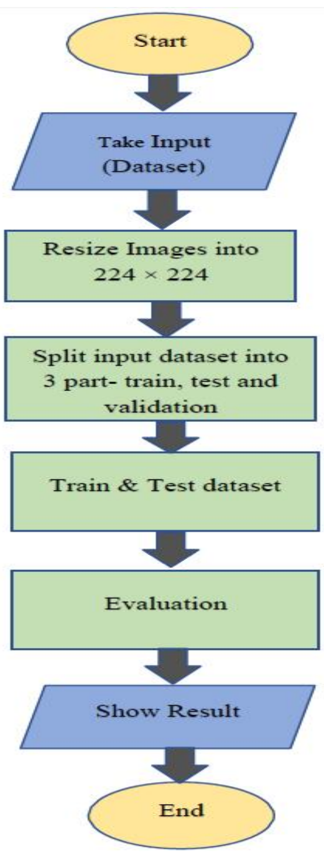

Fig 3.1: Workflow Diagram

3.4 Data CollectionProcedure

We collected data from sources that are reliable and ready to use. We took vast help from google that made sure we get our plant images accordingly. We took 100 images for each plant and as it stands we collected a total of 500 images for 5 plants species which are fruits. There are many sources on the internet from where we can collect data. More images we collect the more accurate will be the result as it train more and more and to give us a solid result. We had to resize every images into 224*224 pixels so that it can viewed using a laptop.

3.5 Proposed Methodology

We used CNN model to detect the images. Many model can be used for image classification in CNN but we used classic CNN model in our work thus strengthening the accuracy rate with other factors. Also CNN is not very time consuming and easy to use. It is mostly used now-a-days for image classification as it recently gained its momentum of being one of the best image processing models. The steps which are to be followed for getting the desired result is mentioned below.

Dataset Modification: Dataset modification refers to the process of altering the characteristics of a dataset before using it to train a CNN model. This can include techniques such as sampling, which involves selecting a subset of the data to use for training, or dimensionality reduction, which involves removing redundant or irrelevant features from the data. Modifying the dataset can help to improve the performance of the model by reducing the complexity of the data and making it easier for the model to learn and make predictions. It can also help to reduce the training time and computational resources required by the model.

Data pre-processing: Data pre-processing is an important step in building a CNN model. It involves cleaning and formatting the data, as well as scaling and normalizing it so that it can be used effectively by the model. This can include tasks such as removing missing or corrupted values, one-hot encoding categorical variables, and spliting the data into training and testing sets. Pre-processing the data helps to ensure that the model is able to learn and make accurate predictions from the data.

Model Implementation: Model implementation refers to the process of building and training a CNN model using a dataset. This can involve selecting an appropriate model architecture, configuring the model hyperparameters, and compiling the model with a chosen loss function and optimizer. Once the model is compiled, it can be trained on the dataset using a batch size and number of epochs specified by the user. During training, the model processes the input data and updates the model parameters to minimize the loss and improve the model's performance.

Performance evaluation: Performance evaluation is the process of assessing the accuracy and effectiveness of a CNN model on a given dataset. This can involve calculating evaluation metrics such as accuracy, precision, and recall, and comparing the model's performance to a baseline or to other models. Performance evaluation can be done on the training data, the validation data, or the test data, depending on the specific requirements and goals of the project. By evaluating the performance of the model, it is possible to identify any problems or areas for improvement and to determine whether the model is ready for deployment.

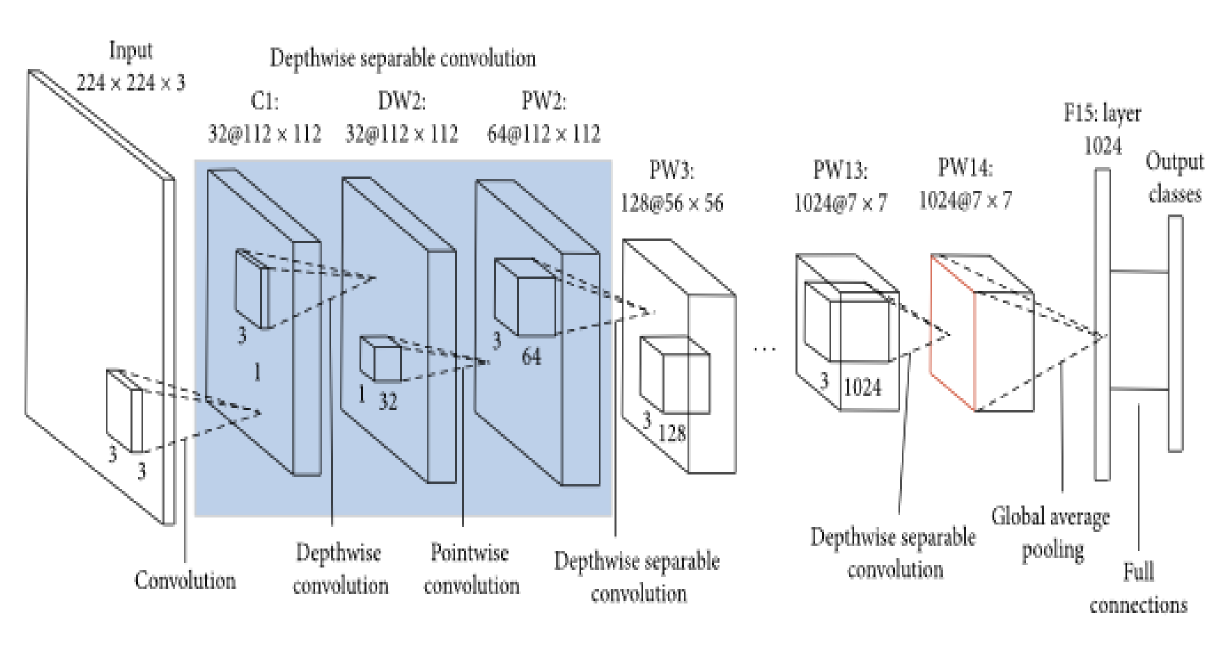

Fig 3.2: Another CNN Model For Image Classification

Other models for image classification in CNN:

1. **LeNet:** This is an early CNN model created by Yann LeCun and colleagues in the 1990s. It was designed for handwritten digit recognition and consists of a series of convolutional and pooling layers, followed by fully connected layers.

2. **AlexNet:** This CNN model was developed by Alex Krizhevsky and colleagues and was the winner of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. It introduced the use of rectified linear units (ReLUs) as non-linear activation functions and the use of dropout for regularization.

3. **VGG:** This CNN model, developed by Karen Simonyan and Andrew Zisserman, was a runner-up in the ILSVRC 2014 competition. It consists a number of convolutional and pooling layers, with a very small number of filters in each layer, which allows it to learn very low-level features.

4. **ResNet:** This CNN model, developed by Kaiming He and colleagues, was the winner of the ILSVRC 2015 competition. It introduced the use of reconnections which can help alleviate the problem of vanishing gradients in deep networks.

5. **MobileNetV2:** MobileNetV2 is a lightweight CNN model designed for efficient on-device image classification. The model is characterized by its depthwise separable convolutions, which allow it to achieve good performance with a low number of parameters and computational resources.

We discussed about the proposed methodology and our working procedure. We are sure to get a good result by using CNN method for image classification. The accuracy rate and loss will be higher and lower respectively if we do our work accordingly and precisely. Our main focus will be to get accuracy as much as we can. Also the image resizing has to be done in a fixed way which will help the model to classify image properly. The things which will be done has been described in the upper level of this chapter and also the working procedure. The rest will be mentioned in our results which will be below the pages. We first tried with MobileNetV2 model for image classification and cross validation but we could not get our desired result as it was showing error all the time. Then we had to use CNN model directly in order to get the cross-validation. Otherwise it would not been possible to get the desired result that we hoped for. It took us some time but we were able to do in the best way possible.

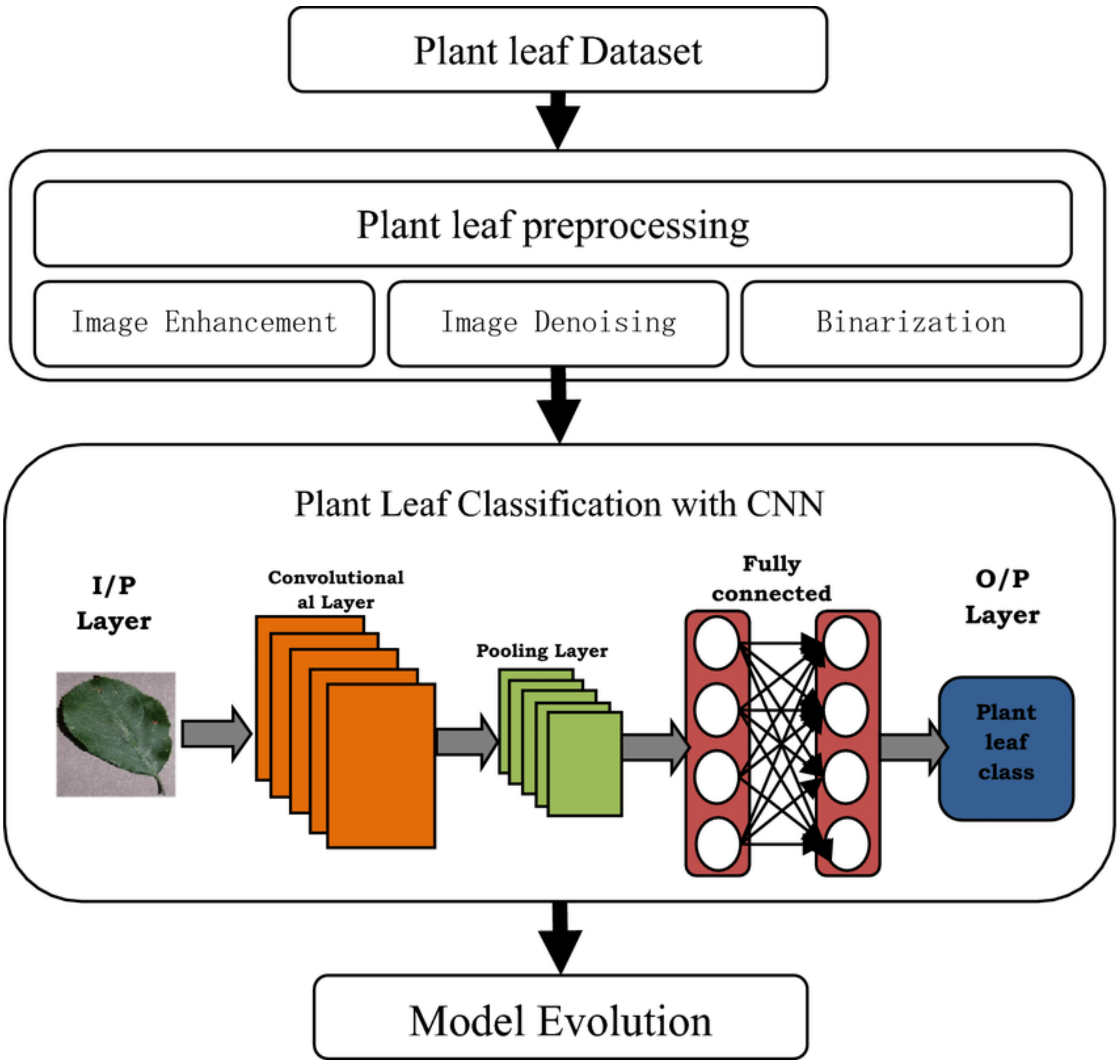

Fig 3.3: A visual representation of how image classification works

Convolutional Neural Network (CNN): The fundamental reason for utilizing the CNN method is that it is the only algorithm that accepts images as input and draws a feature map based on the input pictures, classifying each pixel based on similarity and differences. The CNN identifies the pixels and generates a feature map, which is a matrix. These matrices are crucial in determining the essence of the object in the input image. In the CNN paradigm, we can see layers of three types : 1. Convolutional, 2. Pooling, 3. Fully connected.

3.3.1 Convolutional: A convolutional layer consists of a set of filters, which are used to scan over the input data and extract features. Each filter is a small matrix of weights, and the convolution operation involves multiplying the filter weights by the values in the input data and summing the results. This process is repeated at each location in the input data, and the output of the convolution is a feature map.

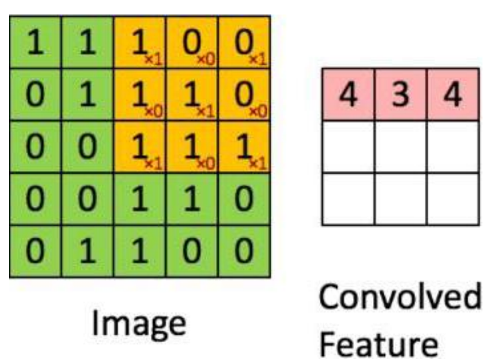

Fig 3.5: Convolutional Layer Effect

3.3.2 Max Pooling: In Convolutional Neural Networks, Max Pooling is a down sampling approach. The goal is to reduce the dimensionality of an input representation by down sampling it, allowing assumptions to be made about characteristics included in the binned sub-regions. It is mostly used to minimize image size because a bigger number of pixels contributes to more parameters, which can result in vast amounts of data.

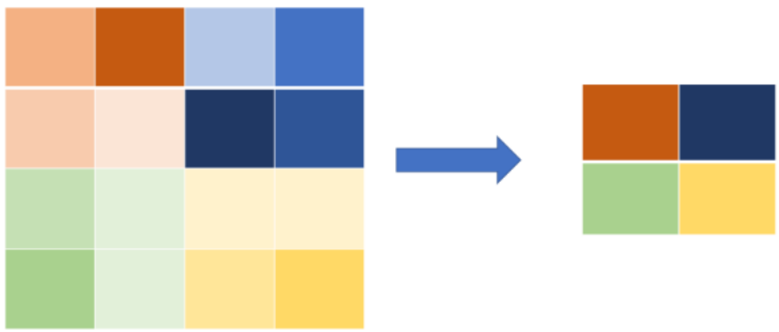

Fig 3.6: Max Pooling

3.3.3 Fully Connected: Dense layer is simply a synonym for a fully connected layer. In the dense layer, where every neuron is coupled to the others, similar actions take place. It's also known as dense because it's made up of a lot of dense neurons. Each neuron pair in a dense layer has a different weight, and each pair has a different value. Various types of functions, such as the softmax activation function, SVM, and others, are utilized in the neural network for high-level reasoning. These characteristics of the input images are used to categorize and investigate different categories. When the convolution layer's characteristics and the polling layer's features are combined, the result is superior.

Advantages of CNN Model

- **Ability to process data with a grid-like topology:** CNNs are designed to process data with a grid-like topology, such as an image, which makes them well-suited for tasks such as object recognition and classification

- **Local connectivity:** CNNs use local connectivity, meaning that each neuron in a layer is only connected to a small region of the layer below it. This allows them to learn spatial hierarchies of features, which is important for image processing tasks.

- **Translation invariance:** CNNs are translation invariant, meaning that they are able to recognize an object regardless of its position in the image. This is because they use shared weights and biases, which allows them to detect patterns anywhere in the input data.

- **Shared weights and biases:** CNNs use shared weights and biases, which means that the same set of weights and biases is used at each location in the input data. This allows them to learn features that are useful for multiple different tasks, and can also help reduce the number of parameters in the model.

- **Good performance on a wide range of tasks:** CNNs have been shown to perform well on a wide range of image processing tasks, including object recognition, classification, and segmentation.

Disadvantages of CNN:

- **Need for large amounts of labeled data:** CNNs typically require a large amount of labeled data in order to learn effectively. This can be a challenge in situations where it is difficult to obtain a large labeled dataset.

- **Sensitivity to the scale and orientation of input data:** CNNs are sensitive to the scale and orientation of the input data, and may not perform well on images that are significantly larger or smaller than the training data, or that are rotated or flipped.

- **Lack of interpretability:** CNNs are typically considered to be black box models, meaning that it is difficult to understand why a particular prediction was made. This can make it difficult to debug the model or to understand its limitations.

- **Computational requirements:** CNNs can be computationally intensive to train and run, which can be a challenge in situations where computational resources are limited.

- **Overfitting:** Like other machine learning models, CNNs are susceptible to overfitting, especially when the training dataset is small or not representative of the test data. This can lead to poor generalization .

Why we should use CNN model:

The main reason behind CNN is feature engineering is not required. When we compare handcrafted features with CNN, CNN performance well and gives better accuracy. It covers local and global components. It also learns different parts from images. In algorithm-based image classification, we need to select the features (local, global) and classifiers. In some cases, global features work well, and in some cases, local features work well**.** Thus, it makes our work more easy than other models.

3.3.4 Other Models For Image Classification:

- **(ANNs):** Artificial Neural Networks (ANNs) are a type of ML technique model made from the structure and function of the human brain. They consist of a large number of interconnected processing nodes, which are organized into layers. Each node receives input from other nodes, processes the input using a simple computation, and sends the result to other nodes in the next layer. ANNs are trained using a large dataset and an optimization algorithm. ANNs are capable of

- **(GNNs):** Generative Adversarial Networks (GANs) are a type of machine learning model that consists of two neural networks: a generator and a 19 discriminator. The generator is trained to produce synthetic data that is similar to a target dataset, while the discriminator is trained to distinguish between real and generated data. GANs have been used to generate a wide range of synthetic data, including images, text, and audio. They are particularly useful for tasks where it is difficult to obtain a large amount of real training data, such as generating realistic images of objects or people that do not exist.

- **Autoencoders:** Autoencoders are a type of neural network that are trained to reconstruct their input data. The encoder processes the input data and produces a compact representation, called the encoding, which is typically smaller than the original input. The decoder then takes the encoding as input and produces a reconstruction of the original data. Typically, it uses an optimization algorithm such as gradient descent. Autoencoders can be used for tasks such as image compression and denoising, and can also be used as a tool for learning meaningful representations of data for other tasks, such as classification.

- **Transfer learning**: It is a technique in which a pre-trained machine learning model is used as the starting point for a new task, rather than training a model from scratch. Transfer learning can be applied to a variety of model types, including convolutional neural networks (CNNs) and natural language processing (NLP) models. To use transfer learning, the pre-trained model is typically first fine-tuned on a small dataset for the new task, using techniques such as adjusting the learning rate or adding additional layers to the model.

Implementation Requirement

To implement the Model that we proposed here the following steps should be followed:

Step 1: The first and foremost work is to select the preferred dataset for our work. As we collected 100 images for each therefore that be enough for each plant.

Step 2: Then we should prepare our dataset for training and resizing them into 224*224.

Step 3: After that training data is created which contains image values.

Step 4: Shuffle the dataset after training them.

Step 5: Then we have to assign labels and features which will be used for classification.

Step 6: Normalizing X and converting labels to categorial data.

Step 7: Split X and Y for use in CNN.

Step 8: Then we need to define, compile and train the CNN model.

Step 9: Lastly we need to add accuracy and score of the model.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 ExperimentalSetup

We are using Google Colab for our experimental setup. In colab we have completed all our works fully. Firstly we read all the files. Library importing is done after that. Then the data is being showed. After showing the data we count the total number of leaves. Then a new folder is being created where we keep the images. After that we are to resize our data. After resizing we can see the image that is resized. The picture of both before resizing and after resizing into 224*224 parameters the results are shown.

4.2 PerformanceAnalysis

As we discussed earlier we are going to resize the image first and then we will continue to work with our images by labelling and scalling them accordingly.

Fig 4.1: Image Dataset

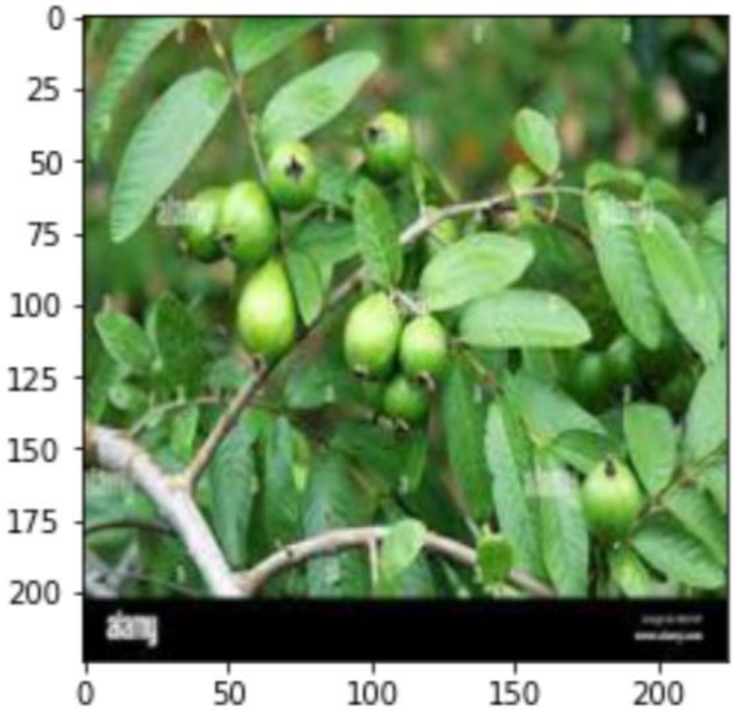

Fig 4.2: Image Dataset after resizing

Here we can see that in fig that the image is not in given parameter and after resizing it we got it into our respective parameter for our work. After preparing the resized image we scale and label our images. Resizing is done mainly because every device has some certain parameter to maintain and that's what we have done we have converted our images into 224*224 pixels so that our laptop can read the image in a specific manner. After that we give the epoch number upto 8 to arouse from any error that might occur during finding the accuracy. Cross validation accuracy is also found in the same way and thus we have got the accuracy, loss and validation accuracy.

Train-test value: The train and test value is provided below

```
/usr/local/lib/python3.8/dist-packages/tensorflow/python/util/dispatch.py:1082: UserWarning: "`sparse_categorical_crossentropy` rece
  return dispatch_target(*args, **kwargs)
11/11 [==============================] - 24s 2s/step - loss: 2.7689 - accuracy: 0.2000 - val_loss: 1.7456 - val_accuracy: 0.2
Epoch 2/20
11/11 [==============================] - 19s 2s/step - loss: 1.5910 - accuracy: 0.3143 - val_loss: 1.6572 - val_accuracy: 0.2267
Epoch 3/20
11/11 [==============================] - 19s 2s/step - loss: 1.5094 - accuracy: 0.2857 - val_loss: 1.6056 - val_accuracy: 0.2733
Epoch 4/20
11/11 [==============================] - 19s 2s/step - loss: 1.3404 - accuracy: 0.5286 - val_loss: 1.6328 - val_accuracy: 0.2800
Epoch 5/20
11/11 [==============================] - 19s 2s/step - loss: 1.1501 - accuracy: 0.5714 - val_loss: 1.6447 - val_accuracy: 0.2867
Epoch 6/20
11/11 [==============================] - 21s 2s/step - loss: 0.8666 - accuracy: 0.7171 - val_loss: 1.8523 - val_accuracy: 0.2867
Epoch 7/20
11/11 [==============================] - 19s 2s/step - loss: 0.6014 - accuracy: 0.8457 - val_loss: 1.7644 - val_accuracy: 0.2933
Epoch 8/20
11/11 [==============================] - 19s 2s/step - loss: 0.3861 - accuracy: 0.9229 - val_loss: 2.0610 - val_accuracy: 0.2867
Epoch 9/20
11/11 [==============================] - 20s 2s/step - loss: 0.2028 - accuracy: 0.9771 - val_loss: 2.1200 - val_accuracy: 0.2800
Epoch 10/20
11/11 [==============================] - 22s 2s/step - loss: 0.0904 - accuracy: 0.9886 - val_loss: 2.2802 - val_accuracy: 0.2800
Epoch 11/20
11/11 [==============================] - 20s 2s/step - loss: 0.0534 - accuracy: 0.9914 - val_loss: 2.4619 - val_accuracy: 0.2733
Epoch 12/20
11/11 [==============================] - 20s 2s/step - loss: 0.0459 - accuracy: 0.9914 - val_loss: 2.6368 - val_accuracy: 0.2467
Epoch 13/20
11/11 [==============================] - 20s 2s/step - loss: 0.0366 - accuracy: 0.9914 - val_loss: 2.9338 - val_accuracy: 0.2867
Epoch 14/20
11/11 [==============================] - 20s 2s/step - loss: 0.0535 - accuracy: 0.9914 - val_loss: 2.5629 - val_accuracy: 0.2933
Epoch 15/20
11/11 [==============================] - 22s 2s/step - loss: 0.0526 - accuracy: 0.9914 - val_loss: 2.7304 - val_accuracy: 0.2667
Epoch 16/20
11/11 [==============================] - 20s 2s/step - loss: 0.0292 - accuracy: 0.9943 - val_loss: 2.9077 - val_accuracy: 0.3067
Epoch 17/20
11/11 [==============================] - 20s 2s/step - loss: 0.0316 - accuracy: 0.9943 - val_loss: 2.8350 - val_accuracy: 0.2733
Epoch 18/20
11/11 [==============================] - 22s 2s/step - loss: 0.0215 - accuracy: 0.9943 - val_loss: 2.5375 - val_accuracy: 0.2667
Epoch 19/20
11/11 [==============================] - 20s 2s/step - loss: 0.0173 - accuracy: 0.9943 - val_loss: 2.6829 - val_accuracy: 0.2667
Epoch 20/20
11/11 [==============================] - 20s 2s/step - loss: 0.0327 - accuracy: 0.9943 - val_loss: 2.6370 - val_accuracy: 0.2933
```

```
cnn.evaluate(X_test_scalled,y_test)

5/5 [==============================] - 2s 380ms/step - loss: 2.6370 - accuracy: 0.2933
[2.6370105743408203, 0.2933333218097687]
```

Fig 4.3: Train-Test Result

```
Epoch 1/8
11/11 [==============================] - 22s 2s/step - loss: 4.0563 - accuracy: 0.1371 - val_loss: 1.9881 - val_accuracy: 0.1867
Epoch 2/8
11/11 [==============================] - 22s 2s/step - loss: 1.7761 - accuracy: 0.1914 - val_loss: 1.5880 - val_accuracy: 0.2533
Epoch 3/8
11/11 [==============================] - 24s 2s/step - loss: 1.5720 - accuracy: 0.3286 - val_loss: 1.6244 - val_accuracy: 0.2467
Epoch 4/8
11/11 [==============================] - 21s 2s/step - loss: 1.3694 - accuracy: 0.4600 - val_loss: 1.5428 - val_accuracy: 0.3133
Epoch 5/8
11/11 [==============================] - 21s 2s/step - loss: 1.1759 - accuracy: 0.5571 - val_loss: 1.7421 - val_accuracy: 0.2933
Epoch 6/8
11/11 [==============================] - 21s 2s/step - loss: 0.9812 - accuracy: 0.6771 - val_loss: 1.5106 - val_accuracy: 0.3867
Epoch 7/8
11/11 [==============================] - 21s 2s/step - loss: 0.6145 - accuracy: 0.8686 - val_loss: 1.8510 - val_accuracy: 0.3600
Epoch 8/8
11/11 [==============================] - 21s 2s/step - loss: 0.4072 - accuracy: 0.9000 - val_loss: 1.6690 - val_accuracy: 0.3533
```

As we said we have given 8 epoch to arouse from any kind of error to happen and also we don't want 100% accuracy to come.

```
5/5 - 2s - loss: 2.3099 - accuracy: 0.3667 - 2s/epoch - 420ms/step
```

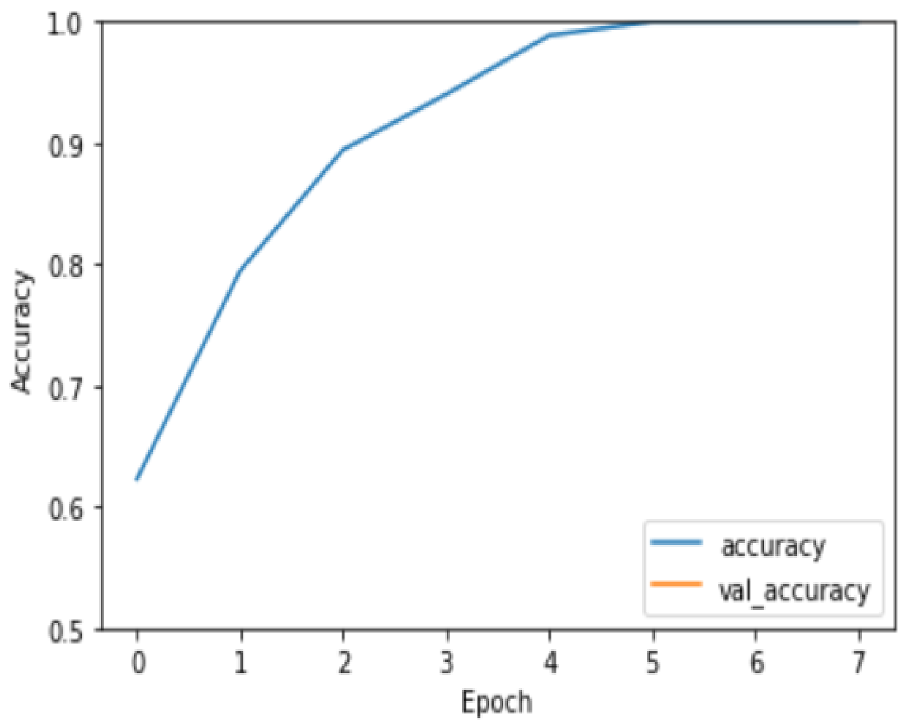

Fig 4.4: Accuracy Rate

This is graph of accuracy and as you can see we have enough accuracy compared to our given data. We need to collect more data in order to get more accuracy. The validation accuracy is close to 37% which is quite good compared to the amount of data that we provided during our work. Therefore, we are to collect more data to get more accuracy.

Classification Report:

	precision	recall	f1-score	support
0	0.22	0.54	0.31	24
1	0.73	0.25	0.37	32
2	0.40	0.46	0.42	37
3	0.45	0.31	0.37	32
4	0.53	0.32	0.40	25
accuracy			0.37	150
macro avg	0.47	0.38	0.38	150
weighted avg	0.47	0.37	0.38	150

Fig 4.5: Classification Report

So this is the final classification report of the 5 fruits that we are working on. We get the precision, recall, f1-score and support result of the following fruits. We got the accuracy 37%. We were expecting more but due to less dataset collecting we could not get our desired accuracy which should be more than 70%. Also, the noise of data is more and that's another issue for getting less accuracy. We are working on it and hopefully we will bring more specific and positive result as we will continue to work on this.

4.3 ResultDiscussion

Therefore, we can see that our cross validation accuracy has come less and we also discussed about the issues that are behind it. We need to ensure proper accuracy and for that we need more train and test dataset. The more the dataset the more accurately will the machine give us results. The main focus will be the to maintain the accuracy for now and do more work as the time emerges toward our finishing point. Also, we are to add more fruits and work on different species in the near future. We hope to make this system a workable one by forming it as an app. By this, children can learn more about different species and know about their classification and features as said earlier. The future is AI and we are just sharing a hint of it rather than the whole sea which lies ahead of us. The more we train and evaluate this model the more it will efficient for us and everybody around us to use it for their own purposes.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact onSociety

The impact of paper "Plant Species Classification using Neural Network" on society is significant, as it has the potential to greatly improve our understanding of plant species and their characteristics. By using neural networks to classify plant species, researchers can more efficiently and accurately understand the relationships between different plant species and their characteristics. This knowledge is important for a variety of purposes, including conservation efforts, the development of new plant-based products, and the identification of potential medicinal plants. For example, a more accurate classification of plant species can help conservationists identify and protect endangered species, while also helping to prevent the extinction of other species. In addition, an easy way to understand plant species and their characteristics can lead to the development of new plant-based products, such as food, medicine, and other consumer goods. This can have a positive impact on society by providing new sources of income and employment for communities that rely on the harvesting and processing of plants. Overall, the use of neural networks for plant species classification has the potential to significantly impact society by improving our understanding of plant species and their characteristics. This knowledge can be used to benefit society in a variety of ways, including conservation efforts, the development of new plant-based products, and the identification of potential medicinal plants

5.2 Impact on the Environment

The classification of plant species is an important aspect of understanding and preserving the natural environment. By accurately identifying and classifying plant species, researchers can better understand the relationships between different plant species and their roles in the ecosystem. The use of neural networks for plant species classification has the potential to vastly improve the accuracy and efficiency of this process. By automating the classification process and allowing for the consideration of a wider range of characteristics, neural networks can provide a more comprehensive and accurate understanding of plant species and their relationships. This improved understanding can have significant impacts on the environment. For example, it can aid in the conservation and protection of rare or endangered plant species, as well as the identification of invasive species that may pose a threat to native plants. In addition, the use of neural networks for plant species classification can also aid in the development of sustainable agriculture practices, as it allows for a better understanding of the characteristics and needs of different plant species. Overall, the use of neural networks for plant species classification has the potential to greatly enhance our understanding of the natural environment and the relationships between different plant species. This understanding can be used to aid in the conservation and protection of plant species, as well as the development of sustainable agriculture practices, ultimately benefiting the environment.

5.3 EthicalAspects

There is a risk that the use of neural networks could result in the loss of jobs for human researchers, as the classification process would be automated. This could potentially lead to unemployment and financial hardship for those affected. To address this concern, it is important that researchers consider the ethical implications of using neural networks and take steps to minimize the negative impact on human workers. This could include providing training and support for those affected by the transition to artificial intelligence, as well as ensuring that the use of neural networks does not result in any discrimination or disadvantage for certain groups of people. Another ethical issue to consider is the accuracy and reliability of the classification process. It is important that the results obtained using neural networks are accurate and reliable, as incorrect classification could have significant consequences for the research and understanding of plant species. To ensure the accuracy and reliability of the classification process, it is important that the neural networks are thoroughly tested and validated before being used for classification. Overall, it is essential that the ethical aspects of using neural networks for plant species classification are carefully considered and addressed in order to minimize any negative impacts and ensure the accuracy and reliability of the classification process.

5.4 SustainabilityPlan

The main aspect of this sustainability plan is the use of non-invasive methods for collecting data. Traditional methods of plant classification often involve collecting samples of plants, which can have negative impacts on the environment and potentially harm the plants themselves. By using neural networks, which do not require the physical collection of samples, we can minimize these impacts and ensure the sustainability of plant species. Another aspect of this sustainability plan is the use of open access databases for the data collected through this research. By making this data publicly available, other researchers and organizations can use it to further their own research and conservation efforts, leading to a greater understanding of plant species and their relationships. Finally, it is important to consider the long-term maintenance and updates of the neural networks used in this research. By regularly updating and improving the accuracy of these networks, we can ensure that they continue to be a valuable tool for plant species classification in the future. Overall, the sustainability plan for this research involves the use of non-invasive methods, the sharing of data through open access databases, and the ongoing maintenance and improvement of the neural networks used. By implementing these measures, we can ensure the sustainability of this research and the preservation of plant species for future generations.

CHAPTER 6

Summary, Conclusion, Recommendation, Implication for Future Research

6.1 Summary of the study

Neural networks are a type of artificial intelligence that can be trained to recognize patterns and classify objects, and they have the ability to learn and improve their accuracy over time. The study will compare the results obtained using neural networks to those obtained using traditional methods in order to determine if neural networks offer any significant advantages. We comprised data and put it in consideration that it is not oversized and the results come accurately. The findings of this study will be valuable for researchers in the field of botany, as it will allow for a more efficient and accurate classification process, leading to a better understanding of the relationships between different plant species and their characteristics.

6.2 Conclusions

The use of neural networks resulted in a more objective classification process, reducing the subjectivity that can often occur in traditional methods. This is especially important in cases where multiple researchers are involved in the classification process, as individual bias can influence the results. Overall, the results of this study demonstrate the effectiveness of using neural networks for plant species classification. They offer numerous benefits, including speed, accuracy, and objectivity, making them a valuable tool for researchers in the field of botany. In conclusion, the use of neural networks for plant species classification is a promising alternative to traditional methods and offers numerous advantages. It is expected that this technology will continue to be used and further developed in the future, leading to even more accurate and efficient classification of plant species.

6.3 Implication for FutureStudy

By accurately identifying and classifying plant species, researchers can better understand the relationships between different plants, as well as their ecological and evolutionary histories. In addition, the ability to accurately classify plant species can have practical applications in areas such as agriculture, forestry, and conservation. However, further research is needed to fully understand the capabilities and limitations of using neural networks for plant classification. For example, additional studies could explore the use of

different types of neural networks, such as convolutional neural networks or recurrent neural networks, and compare their effectiveness. Additionally, research could examine the use of various types of input data, including images, genomic data, and morphological data, to determine the most effective methods for plant classifications.

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APPENDICES

We had a lot of challenges finishing the research study. The first step was choosing a methodological strategy for the project. However, the largest problem we ran into during the research was that, as computer science majors, we lacked a solid understanding of virology and the cell chemistry of the virus. By researching and examining relevant and prior efforts in that field, we were able to overcome this challenge. The best dataset for our model to work on needed to be created as our next assignment. The raw dataset we obtained from the database source was a FASTA file, which deep learning classifiers cannot read. So, to make the dataset readable by a deep learning classifier, we had to change the dataset's file format from FASTA to CSV.

Final_Defense report

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