

ANALYSIS OF AN EFFICIENT CNN ALGORITHM FOR AGRICULTURE APPLICATIONS

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Engineering degree in Electronics and Communication Engineering

By

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION
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SCHOOL OF ELECTRICAL AND ELECTRONICS

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Manuvanth S (40130709)** and **Revanth CH (40130279)** who carried out the Project entitled **"ANALYSIS OF EFFICIENT CNN ALGORITHM FOR AGRICULTURE APPLICATIONS"** under our supervision from January 2024 to April 2024.

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We Manuvanth S (Reg.No- 40130709), Revanth Ch (Reg.No-40130279) hereby declare that the Project Report entitled "**ANALYSIS OF EFFICIENT CNN ALGORITHM FOR AGRICULTURE APPLICATIONS**" done by us under the guidance of Dr.G.JEGAN, M.E.,Ph.D , Associate Professor Dept. of Electronics and Communication Engineering, Sathyabama Institute of Science and Technology, Chennai is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineering.

reviews.

We would like to express our sincere and deep sense of gratitude to our Project Guide Dr.G.JEGAN, M.E., Ph.D., Associate Professor Dept. of Electronics and Communication Engineering for his valuable guidance, suggestions and constant encouragement paved way for the successful completion of our project work.

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ABSTRACT

This project presents a comprehensive analysis of an efficient Convolutional Neural Network (CNN) algorithm designed specifically for agriculture applications. The integration of cutting-edge technologies, such as computer vision and deep learning, in agriculture is essential for sustainable practices and improved crop management. The proposed CNN algorithm addresses the unique challenges faced in agriculture, including varying lighting conditions, vegetation occlusions, and diverse crop types. Its architecture is carefully optimized to maximize accuracy while minimizing computational resources and memory usage, making it suitable for deployment on resource-constrained edge devices in rural agricultural settings. Extensive experiments are conducted on diverse datasets containing images of different crops, pests, diseases, and environmental conditions to evaluate the algorithm's performance. The results demonstrate that the proposed CNN algorithm outperforms existing state-of-the-art models in terms of accuracy and computational efficiency. The practical implications of the efficient CNN algorithm in real-world agricultural applications are discussed. Its potential to automate tasks such as crop monitoring, pest detection, disease identification, and yield prediction is explored, highlighting its role in optimizing agricultural practices, minimizing resource wastage, and increasing overall productivity. The algorithm's scalability and adaptability are considered, enabling it to accommodate emerging agricultural technologies and advancements in computer vision. The analysis reveals the significance of the efficient CNN algorithm for revolutionizing agriculture practices. By harnessing the power of deep learning and optimizing computational efficiency, this algorithm paves the way for sustainable and data-driven agriculture, contributing to global food security and resource conservation.

TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.
	ABSTRACT	V
	LIST OF FIGURES	VIII
1	INTRODUCTION	1
	1.1 ROLE OF DIGITAL IMAGE PROCESSING IN AGRICULTURE APPLICATIONS	2
	1.1.1 PRECISION AGRICULTURE	2
	1.1.2 CROP MONITORING AND MANAGEMENT	2
	1.1.3 PRODUCT QUALITY AND SORTING	3
	1.2 PADDY DISEASES	3
	1.2.1 BACTERIAL BLIGHT	3
	1.2.2 BROWN SPOT	3
	1.2.3 BLAST	3
	1.2.4 TUNGRO	3
	1.2.5 DEAD HEART	4
	1.2.6 DOWNY MILDEW	4
	1.2.7 HISPA	4
	1.3 AIM	4
	1.4 SCOPE	4
2	LITERATURE REVIEW	6
	2.1 INFERENCES FROM LITERATURE SURVEY	6
	2.2 CLASSICAL IMAGE PROCESSING BASED MODEL	6
	2.3 DEEP LEARNING BASED MODEL	8
3	EXPERIMENT, MATERIAL & METHODS	11
	3.1 DATASET	11
	3.2 METHODOLOGY	16
	3.2.1 BLOCK DIAGRAM	16

	3.3 ARCHITECTURE OF THE MODEL	17
	3.3.1 CONVOLUTINAL LAYERS	17
	3.3.2 POOLING LAYERS	18
	3.3.3 FULLY CONNECTED LAYERS	18
	3.4 MACHINE LEARNING MODELS BASED ON DEEP FEATURES	19
4	RESULT AND DISCUSSION	20
	4.1 DENSENET ARCHITECTURE	21
	4.2 MODEL ACCURACY AND LOSS GRAPH	22
	4.2.1 RESNET-50	22
	4.2.2 ALEXNET	25
	4.2.3 GOOGLNET	27
	4.2.4 RESNET-101	29
	4.2.5 XCEPTION	32
	4.2.6 NASNET MOBILE	35
	4.2.7 DENSENET-201	38
	4.3 MODIFIED DENSENET	41
	4.4 RESULT TABLE AND CHART	44
5	CONCLUSION	45
	REFERENCE	46

LIST OF FIGURES & TABLES

CHAPTER NO.	FIGURE NAME	PAGE NO.
3.1	BACTERIAL BLIGHT	12
3.2	BROWN SPOT	12
3.3	DEAD HEART	13
3.4	DOWNY MILDEW	13
3.5	HISPA	14
3.6	LEAF BLAST	14
3.7	TUNGRO	15
3.8	NORMAL	15
3.9	BLOCK DIAGRAM OF CNN	16
3.10	PROPOSED ALEXNET AND GOOGLNET CNN GENERAL ARCHITECTURE	17
3.11	RICE LEAF DISEASE IDENTIFICATION USING THE TRANSFER LEARNING APPROACH	18
3.12	THE IDENTIFICATION OF RICE LEAF DISEASE USING MACHINE LEARNING APPROACHES ON DEEP FEATURES	19
4.1	DENSENET BLOCKS	21
4.2	DENSENET-201 ARCHITECTURE	21
4.3	MODIFIED DENSENET	22
4.4	RESNET-50 MODEL GRAPH	24
4.5	RESNET-50 CONFUSION MATRIX	24
4.6	ALEXNET MODEL GRAPH	26
4.7	ALEXNET CONFUSION MATRIX	27
4.8	GOOGLE MODEL GRAPH	29
4.9	GOOGLE CONFUSION MATRIX	29
4.10	RESNET-101 MODEL GRAPH	31
4.11	RESNET-101 CONFUSION	31
4.12	XCEPTION MODEL GRAPH	34

4.13	XCEPTION CONFUSSION	35
4.14	NASNET MOBILE MODEL GRAPH	37
4.15	NASNET MOBILE CONFUSSION	37
4.16	DENSENET-201 MODEL GRAPH	40
4.17	DENSENET-201 CONFUSSION MATRIX	40
4.18	MODIFIED DENSENET MODEL GRAPH	43
4.19	MODIFIED DENSENET CONFUSSION MATRIX	43
4.20	ACCURACY CHART	44
4.21	ELAPSED TIME CHART	44
T4.1	NETWORKS RESULT	44

CHAPTER 1

INTRODUCTION

Rice stands as one of the key staple crops globally, providing sustenance for over 3.5 billion individuals worldwide. Its cultivation significantly contributes to the agricultural sector and the Indian economy. The prevalence of rice cultivation is highest in Asia, owing to its preference for humid environments over other crops. Nevertheless, rice productivity in India has remained stagnant in recent years, revealing a shortfall despite extensive cultivation. This underscores the inadequacies in modernizing farming practices in India when compared to other Asian nations. Notably, the southern region, encompassing Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu, plays a pivotal role in India's rice production.

Statistics indicate that low rice productivity in India can be attributed to the limited adoption of modern agricultural technology. Disease and pest infestations result in productivity losses ranging from 10% to 20%. A significant factor in the decline of crop production lies in the challenge of detecting disease symptoms in their early stages of infection. Furthermore, distinguishing between symptoms of different diseases proves difficult, as they often appear identical.

Bacterial blight, Leaf blast, Brown spot, Dead heart, Downy mildew, Hispa, and Tungro are the most prevalent diseases affecting rice cultivation in southern India. These diseases exhibit rapid rates of spread. Typically, symptoms manifest on the leaves. Traditional disease identification methods rely on visual observation or experimentation with expert guidance. These approaches are time-intensive and contribute to disease proliferation. Moreover, early stages of infectious diseases are notoriously challenging to detect, leading to substantial losses for farmers.

Early detection of infectious diseases is imperative in curtailing their spread and mitigating overall losses. Various reports suggest that adopting precise farming practices like IT-based farm management systems and precision agriculture (PA) can address these challenges. While numerous studies have explored the use of image processing-based models for rice leaf disease identification, many are heavily

reliant on data availability and susceptible to classification errors due to image resolution and complex backgrounds.

The integration of modern farming technologies and the application of artificial intelligence has yielded accurate and flawless prediction algorithms, akin to the expertise of a specialist. Since 2016, the commercialization of precision farming methods has been a driving force in the field of plant pathology. This research endeavors to assess the suitability of transfer learning with Deep Convolutional Neural Network (DCNN) architectures for precise identification of rice leaf diseases. The authors also investigate the impact of Dynamic Mode Decomposition-based attention-driven preprocessing on disease recognition. A dataset comprising 2,400 images of infected rice leaves sourced from various online platforms, including Kaggle and Plant Village, was employed in this study.

1.1 ROLE OF DIGITAL IMAGE PROCESSING IN AGRICULTURE APPLICATIONS

Digital image processing is revolutionizing the agricultural sector by providing farmers with new tools to analyze and manage their crops. Here are some key areas where it's playing a vital role

1.1.1 PRECISION AGRICULTURE

- **Disease and Pest Detection** Image processing algorithms can analyze photographs taken from drones or satellites to identify signs of crop disease or pest infestation at an early stage. This allows for targeted treatment, minimizing pesticide use and saving crops.
- **Nutrient Deficiency Identification** By analyzing the colour and texture of leaves, image processing can detect nutrient deficiencies in plants. This enables farmers to apply fertilizers only where needed, optimizing resource use and crop health.

1.1.2 CROP MONITORING AND MANAGEMENT

- **Yield Estimation:** Digital analysis of aerial or satellite imagery can estimate crop yield even before harvest. This helps farmers plan logistics, storage, and sales more effectively.

- Crop Health Monitoring: Throughout the growing season, farmers can use image processing to monitor crop health and growth patterns. This allows them to identify problems early and take corrective actions.
- Weed Identification and Control: Image processing can distinguish between crops and weeds, enabling targeted weed control and reducing herbicide use.

1.1.3 PRODUCT QUALITY AND SORTING

- Fruit and Vegetable Grading: Cameras and image processing software can sort fruits and vegetables based on size, color, ripeness, and defect detection. This ensures consistent quality and maximizes product value.

Overall, digital image processing is transforming agriculture into a more data-driven and efficient industry. By providing farmers with real-time insights into their crops, it allows them to make informed decisions, optimize resource use, and improve farm yields.

1.2 PADDY DISEASE

Here's a breakdown of some major paddy diseases mentioned

1.2.1 BACTERIAL BLIGHT

- Caused by the bacterium *Xanthomonas oryzae* pv. *oryzae*.
- Symptoms: Water-soaked spots on leaves that turn into streaks, wilting, and yellowing. Often called "kresek" or "seedling wilt".

1.2.2 BROWN SPOT

- Caused by the fungus *Helminthosporium oryzae*.
- Symptoms: Oval or round dark brown spots with a yellow border. Can infect florets and reduce grain quality.

1.2.3 BLAST

- Caused by the fungus *Pyricularia grisea* (previously known as *Magnaporthe grisea*).
- Also called rotten neck or rice fever. A major disease worldwide.
- Symptoms: Grayish-white lesions on leaves, necks, and grains. Can significantly reduce yield.

1.2.4 TUNGRO

- Caused by Rice tungro virus (multiple strains). Spread by leafhoppers.

- Symptoms: Stunted growth, yellow or orange-tinged leaves, sometimes with rust-colored spots. Discoloration starts at the leaf tip and spreads down.

1.2.5 DEAD HEART

- Caused by various factors like nutrient deficiencies, herbicide damage, or fungal infection. Not a single disease.
- Symptoms: White or light-colored dead center of the young shoot, stunted growth, and sterile spikelets.

1.2.6 DOWNY MILDEW

- Caused by the fungus *Sclerophthora oryzae*. Less common than other diseases on this list.
- Symptoms: Greenish-yellow patches on leaves that turn grayish-purple with fungal spores. Can stunt growth and reduce yield.

1.2.7 HISPA

- Not a disease, but a pest - the rice hispa (*Hispa elongata*) beetle.
- Symptoms: Scraped and white-colored patches on leaves due to feeding by adult beetles. Larvae feed inside leaf rolls, causing further damage.

1.3 AIM

The aim of this study is to conduct a comparative analysis of various CNN algorithms, including AlexNet, GoogleNet, VGG16, ResNet101, DenseNet201, ResNet50, NasNet Mobile, and Xception, for the identification of diseases such as bacterial blight, brown spot, dead heart, downy mildew, hispa, leaf blast, and tungro in paddy crops. Utilizing datasets sourced from the internet, the study aims to customize these network architectures to enhance accuracy and reduce the time required for efficient disease identification in paddy crops.

1.4 SCOPE

1. Data Collection

- Acquire datasets related to paddy crop diseases such as bacterial blight, brown spot, dead heart, downy mildew, hispa, leaf blast, and tungro from reliable sources on the internet.

2. Algorithm Selection

- Evaluate and select appropriate CNN algorithms for comparative analysis, including AlexNet, GoogleNet, VGG16, ResNet101, DenseNet201, ResNet50, NasNet Mobile, and Xception.

3. Comparative Analysis

- Implement the selected CNN algorithms to identify the paddy crop diseases.
- Evaluate the performance of each algorithm in terms of accuracy, efficiency, and computational complexity.

4. Customization of Network Architectures

- Modify the architectures of the chosen CNN algorithms to optimize for better accuracy and reduced identification time.
- Implement necessary adjustments to enhance the models' ability to detect specific paddy crop diseases.

5. Evaluation and Validation

- Validate the customized CNN models using the acquired datasets to ensure accurate disease identification.
- Compare the performance of the customized models against the original versions to measure improvements in accuracy and efficiency.

6. Documentation and Reporting

- Compile the findings of the comparative analysis and customization process.
- Prepare a comprehensive project paper detailing the methodology, results, and conclusions of the study.

7. Limitations

- The study will focus solely on the identification of specific paddy crop diseases using the selected CNN algorithms.
- The performance evaluation will be based on the datasets acquired from the internet, which may have limitations in terms of variety and quality.

By adhering to this scope, the project aims to provide insights into the most effective CNN algorithm for the accurate and efficient identification of paddy crop diseases, thereby contributing to advancements in agricultural disease detection techniques

CHAPTER 2

LITERATURE REVIEW

2.1 INFERENCES FROM LITERATURE SURVEY

This section provides a concise summary of contemporary models utilized in the realm of plant disease identification, employing both image processing techniques and deep learning methodologies. The models documented in existing literature can be classified into two primary categories based on their approach: (1) Those grounded in conventional image processing algorithms, and (2) Those founded on deep learning principles.

2.2 CLASSICAL IMAGE PROCESSING-BASED MODELS

Anthony and Wickramarachchi (2009) the authors introduced a disease classification model that relies on segmentation for discerning three distinct types of rice leaf diseases. The initial RGB image is transformed into grayscale, and the Sobel edge extraction method is employed. This process yields images that emphasize solely the affected regions, which are subsequently converted into the *L*ab* format. Features are then extracted and juxtaposed with the membership function for further analysis.[1]

Joshi and Jadhav (2016) the authors explored the effectiveness of the Minimum Distance Classifier (MDC) and K-Nearest Neighbor classifier (KNN) in classifying four common types of rice leaf diseases. Following image pre-processing and segmentation, features such as shape, texture, and color were extracted and subsequently classified using MDC and KNN classifiers.[2]

Singh and Misra (2017) conducted a survey encompassing diverse image segmentation-based classification techniques for the identification of plant diseases. The authors critically evaluated numerous approaches including K-nearest-neighbor, Support Vector Machine, K-means, and Color masking for disease classification. Nevertheless, it was noted that the accuracy of these

models remains suboptimal, with only a small subset of diseases being investigated and a limited dataset available for study.[3]

Islam et al. (2018) a Naive Bayes model is proposed for the classification of plant diseases. The initial step involves preprocessing the original color image to remove extraneous regions. Subsequently, green pixels are masked to accentuate the affected area. The percentage representation of RGB values is then inputted into the Naive Bayes classification model, which categorizes the disease into various classes. It is important to note that this approach is most effective when dealing with a small sample size. Furthermore, for rice diseases, predicting the percentage of RGB value for a specific ailment is challenging due to its dependence on the disease's progression.[4]

Ramesh and Vydeki (2018) introduced an Artificial Neural Network (ANN) based classification model tailored for the binary classification of rice blast disease. To facilitate this, input images undergo pre-processing via Lab colour conversion and HSV colour conversion. The transformed images are subsequently segmented using the K Means clustering algorithm. Statistical attributes including Mean Value, Standard Deviation, and GLCM are computed for both the healthy and infected leaves.[5]

Islam and Mazumder (2019) they introduced a method for extracting features from rice plants based on wavelets. This approach involves decomposing the input image into various sub-bands using inter analysis and Discrete Wavelet Transform (DWT). Pre-processed and segmented images undergo decomposition through a two-dimensional wavelet transform. Classification is then carried out utilizing the Random Subspace method, resulting in an impressive accuracy rate of 95%.[6]

Rath and Meher (2019) cucumber leaf diseases were categorized and assessed through the application of image processing techniques. To glean comprehensive data from the input image, a range of preprocessing methods were employed. Subsequently, segmentation was achieved utilizing the K-means algorithm for classification. The severity of the diseases was quantified by dividing the total leaf area of the plant by the afflicted area.[7]

Bhatia et al. (2020a) the authors introduced an approach employing the Extreme Learning Machine (ELM) algorithm to address imbalanced datasets. Various resampling techniques were employed to balance the dataset. The algorithm's efficacy was assessed on both imbalanced and balanced datasets, with classification accuracy as the metric. It was observed that the performance on the imbalanced dataset was notably inferior when compared to the balanced dataset.[8]

Verma et al. (2020) assessed the performance of capsule networks in classifying potato leaf diseases. In comparison to established pre-trained models like ResNet and VGG16, the capsule networks exhibited superior performance, achieving an accuracy of 91.83%.[9]

Bhatia et al. (2020b) and Shrivastava and Pradhan (2021) the performance of various machine learning algorithms and their combinations was evaluated. In the context of classifying rice leaf diseases, the combination of Support Vector Machine (SVM) and logistic regression demonstrated superior performance compared to other classifiers, including discriminant analysis, K-Nearest Neighbour (KNN), Naive-Bayes, Decision Trees, and Random Forest.[10]

2.3 DEEP LEARNING-BASED MODELS

Grinblat et al. (2016) introduced a plant identification model employing Deep Convolutional Neural Networks (DCNN) based on leaf vein patterns. The extraction of vein morphological patterns from the source image was accomplished through the application of the Hit or Miss transformation method. This model successfully categorized three distinct legume species - white bean, red bean, and soybean, comprising a total of 866 images, utilizing a 6-layer CNN.[11]

Ma et al. (2018) a symptom-based recognition system was created for four cucumber diseases: anthracnose, downy mildew, powdery mildew, and target leaf spots. Field-acquired images were augmented to expand the dataset, and comparative experiments were carried out with both standard classifiers and the AlexNet model. The study concluded that the application of Deep Convolutional

Neural Networks (Deep CNN) proved to be a dependable method for identifying cucumber diseases under field conditions, achieving a success rate of 93.4%.[12]

Sethy et al. (2020) deep features were employed to construct a support vector machine (SVM) classifier for the categorization of diseased leaves. The classifier was trained utilizing deep features extracted from a connected layer of deep Convolutional Neural Networks (CNNs). The authors reported that, in comparison to other CNN models, the combination of Resnet50 and SVM achieved a recognition accuracy of 98.38%.[13]

Jiang et al.'s (2019) study aimed at diagnosing five prevalent types of apple leaf diseases, they introduced the rainbow concatenation approach. The authors proposed a novel model called INAR-SSD, which is integrated into the Inception module using Rainbow concatenation. This technique enhances the capability of deep neural networks to extract features through Rainbow clustering.[14]

Kamal et al. (2019) the authors developed a Reduced MobileNet model tailored for the detection of plant leaf diseases. Due to its lower parameter count compared to the existing MobileNet, this proposed model is particularly well-suited for deployment on handheld devices. In contrast to models like VGG16, the parameter utilization in this model is notably reduced, consequently enhancing its efficiency. The study utilized a dataset of 82,161 images sourced from Plant Village, encompassing 55 distinct classifications of both healthy and diseased plants. The model employs depth-wise separable convolutions, which contributed to achieving high accuracy and improved convergence.[15]

Chen et al.'s (2020) study on rice disease identification, a combination of two distinct CNN models was employed. They harnessed the strengths of both DenseNet, pre-trained on ImageNet, and the Inception module for the classification task. The provided input image underwent preprocessing techniques, including scaling, sharpening, and edge filling, among others. The fully connected layer of DenseNet was substituted with a global max pooling layer, followed by an Inception module and a new fully connected ReLU layer. The authors reported a consistently high average predictive accuracy of no less than 94% on the open dataset.[16]

Deng et al.'s (2021) study, five distinct CNN models - ResNet, DenseNet, SENet, ResNeXt, and ResNeSt - were compared for their effectiveness in classifying rice diseases. The experiment encompassed the examination of 33,026 images representing various rice diseases, including leaf blast, false smut, neck blast, sheath blight, bacterial stripe disease, and brown spot. These five Deep Convolutional Neural Network (DCNN) models were amalgamated to create an Ensemble model, which was subsequently assessed using a smartphone application linked to the network. Additionally, a separate set of images was employed to validate the proposed Ensemble model.[17]

Sunil et al. (2021) a pre-processing strategy utilizing U-Nets was introduced for the identification of diseases in Cardamom plants. The U-Net was utilized to eliminate the complex background from the images. The processed images were subsequently inputted into the EfficientNetV2 model for classification, achieving an impressive accuracy of 98.26%.[18]

Sudhesh K.M, Sowmya V, Sainamole Kurian P, Sikha O.K. (2023) present a novel approach for rice leaf disease identification. Their method, based on dynamic mode decomposition-driven attention preprocessing, tackles challenges arising from symptom similarity and small affected areas. The study evaluates ten transfer-learned deep CNN models, highlighting DenseNet121 with an accuracy of 93.87%. Furthermore, employing deep features from DenseNet121 with a Random Forest classifier outperforms other techniques. The proposed DMD-based preprocessing proves highly effective, achieving 100% accuracy using XceptionNet with an SVM classifier. On-field rice leaf images demonstrate superior classification accuracy of 94.33% with XceptionNet. Models trained on DMD-preprocessed images exhibit markedly improved performance, reflected in Accuracy, Precision, Recall, and F1-Score metrics.[19]

CHAPTER 3

EXPERIMENT, MATERIALS & METHODS

In this project ,we analyze the performance of AlexNet, GoogleNet, VGG16, ResNet101, DensNet201 architectures on the rice leaves-based dataset by adapting already trained models. In this technique, we reconfigure the weights of layers. In the case of AlexNet, ResNet101, DensNet201, and of the loss 3 classifier layers in the case of GoogleNet. In the first phase of the study, the preprocessed images applied as input to the CNN network. The proposed networks retrained for classifying the eight class categories of leaf objects from the defined data set. The last layer was reconfigured and modified, which improves the time taken and accuracy. this study consisted of seven disease and a normal classes, namely bacterial blight, brown spot, Dead Heart, Downy mildew, Hispa, Leaf Blast, Tungro, normal.

3.1 DATASET

The dataset comprises 2400 images of rice leaves sourced from various online platforms, including Kaggle and agricultural pests and insects picture databases. It encompasses eight distinct types of rice leaf diseases examined in this study, namely bacterial blight, brown spot, blast, Tungro, Dead heart, Downy mildew, Hispa, along with healthy variants. To ensure uniformity, the original images were resized to 224×224 pixels. Out of the total images, 300 were allocated for testing, selected randomly with 60 images from each category. Furthermore, 550 images were earmarked for validation. The division of the dataset for training and testing purposes for each category is depicted in the accompanying illustration.



Fig. 3.1. Bacterial blight



Fig. 3.2. Brown spot



Fig. 3. 3. Dead Heart



Fig. 3.4. Downy mildew



Fig. 3.5. Hispa



Fig. 3. 6. Leaf Blast



Fig. 3.7. Tungro



Fig. 3.8. Normal

3.2 METHODOLOGY

We used defined dataset over pre-trained CNN networks for experiments to estimate the effectiveness of our method. Experiment, based on the CNN networks used as both feature extractors and classifiers for the classification. The training epoch adjusted with our proposed method. All of these experiments evaluated under the 5-fold cross-validation strategy. The performance of the proposed network, using the first approach, some training parameters of the CNN networks were modified. The modification included setting the learning rate of the models as 0.0001. The minibatch size set to 64, the number of epochs fixed to 30, and the number of iterations set to 330. The minibatch obtained by splitting the training data set into batches and the gradient descent applied for a network coefficient.

3.2.1 BLOCK DIAGRAM

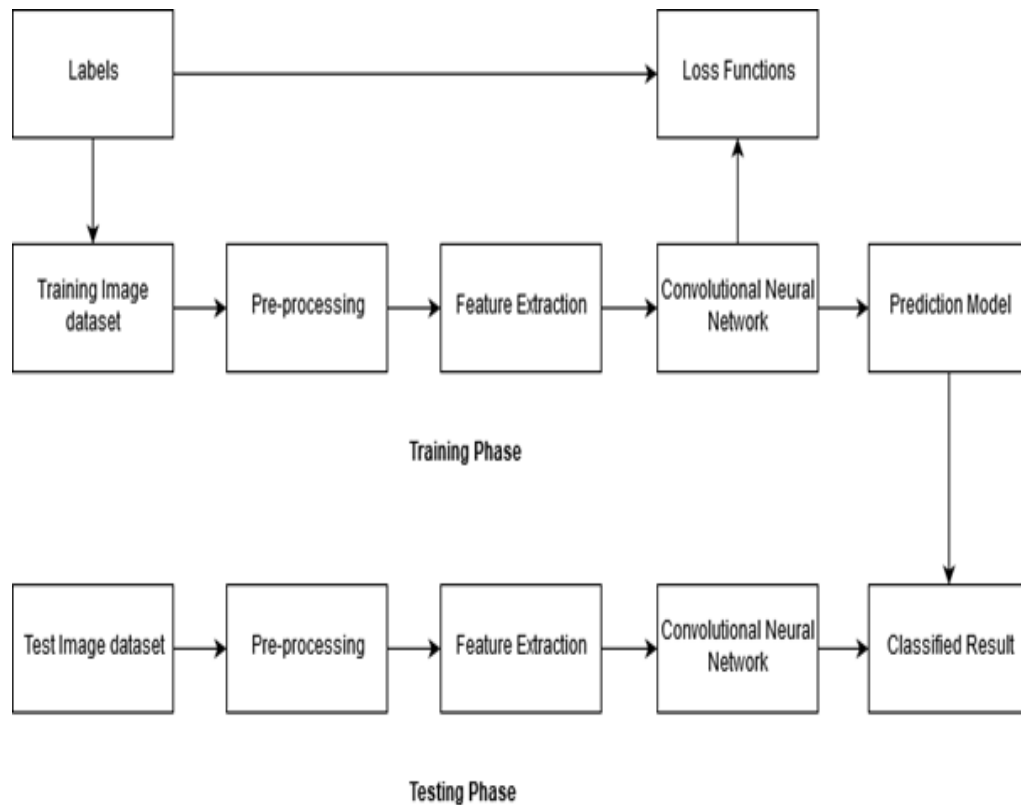


Fig:3.9 Block diagram of CNN

3.3 ARCHITECTURE OF THE CNN MODELS

The AlexNet, GoogleNet, VGG16, ResNet101, and DensNet201 network tested in the experiment problem, which involved the identification of soybean plant diseases from their leaf images. The convolutional neural network passes a raw image through the network layers and provides a final class as an output. The proposed network consists of 3 convolutional layers, each followed by a max-pooling layer. ReLu activation function applied to the output of every convolutional layer and fully connected layer. The proposed networks consisted of fully connected layers, with each layer network learning to detect different features. Filters then applied to each training image at different resolutions, and the output of each convolved image used as the input to the next layer. Brightness and edge features were detected the complexity of features that uniquely define the leaf object increases as the layers progress. Figure 2 shows the proposed pretrained AlexNet, and the GoogleNet general CNN model included three main neural layers, namely convolutional layers, pooling layers, and fully connected layers. The three commonly used neural layers discussed as follows.

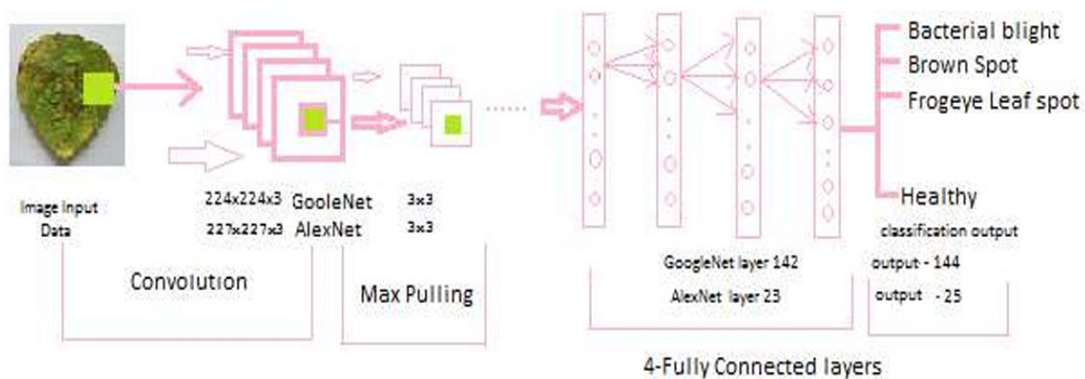


Fig. 3.10. Proposed AlexNet and GoogleNet CNN general architecture

3.3.1. CONVOLUTIONAL LAYERS

Convolution layers process the input images through a set of convolutional filters, each of which activates certain features from the images. Generally, the convolutional layer output represented by

$$M_{j,p} = f(\sum_{i \in M_j} M_{i,p-1} * k_{ij,p} + N_{j,p})$$

Where p represents the p th layer, k_{ij} denotes convolutional kernel, N_j denotes bias, and M_j denotes a set of input maps. The various parameters of architecture, such as the bias and the weight of the kernel, are typically trained using unsupervised learning approach [14, 19]. The raw input image applied to the convolutional layer through a set of filters, each of which activates certain features from the raw input image. In the convolutional layers, a CNN utilizes various kernels to convolve the whole raw input image as well as the intermediate feature maps, generating various feature maps.

3.3.2. POOLING LAYERS

Pooling layers simplify the output by performing nonlinear downsampling, which reduces the number of parameters that the network must learn. In stochastic pooling, the probability p should first compute for each region j according to

$$P_i = \alpha_i \sum_k \varepsilon_j \alpha_k$$

3.3.3. FULLY CONNECTED LAYERS

Fully connected layers “flatten” the network’s 2D spatial features into a 1D vector that represents image level features for classification purposes.

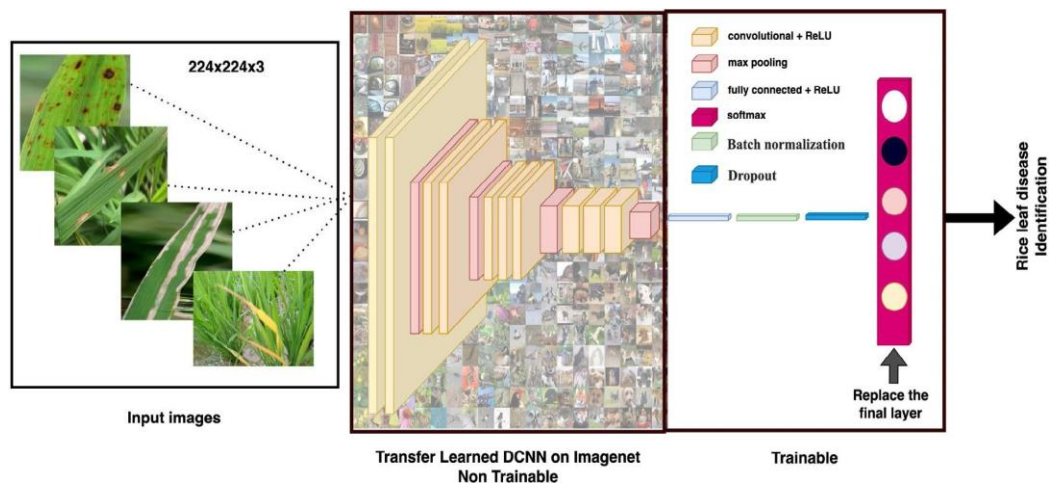


Fig. 3.11. Rice leaf disease identification using the transfer learning approach.

3.4 MACHINE LEARNING MODELS BASED ON DEEP FEATURE

In this section, we delve into the integration of deep convolutional neural networks (CNN) as feature extractors in conjunction with conventional machine learning classification models. This innovative approach leverages the extracted deep features to effectively discern and identify various diseases afflicting rice leaves. By combining the strengths of both D-CNNs and traditional machine learning algorithms, this method holds the promise of enhancing accuracy and reliability in disease classification, marking a significant advancement in the field of plant pathology.

This approach capitalizes on the comprehensive information encoded within the deep features, allowing for a more nuanced and precise characterization of rice leaf diseases compared to conventional methods. Moreover, the synergy between D-CNNs and machine learning models offers a versatile framework capable of accommodating a wide range of disease types and variations, making it a potentially invaluable tool for agricultural practitioners and researchers alike.

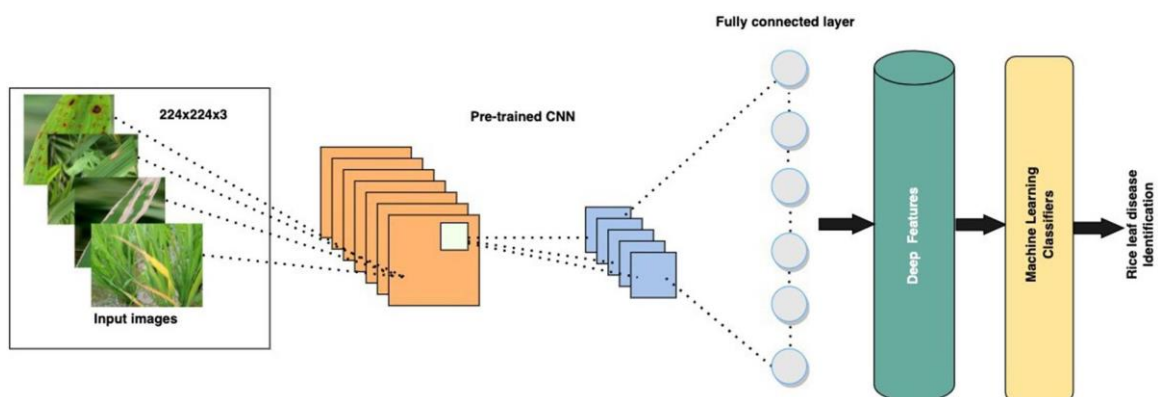


Fig. 3.12. The identification of rice leaf diseases using machine learning approaches on deep features

CHAPTER 4

RESULTS AND DISCUSSION

In this comprehensive study, we conducted an extensive evaluation of the performance of seven distinct deep Convolutional Neural Network (CNN) models for the classification of rice diseases. we meticulously gathered rice disease images from online sources. To ensure uniformity in processing, the original input images were uniformly resized to dimensions of 224×224 pixels. Subsequently, all seven CNN models underwent rigorous training on the meticulously curated dataset, with the training process spanning a total of 6 epochs.

The models were subjected to a comprehensive assessment, considering critical metrics including Training accuracy, Test accuracy, F1 score, Precision, Recall, and Specificity. This rigorous evaluation process enables a thorough understanding of the efficacy and suitability of each deep CNN model in the context of rice disease classification, paving the way for nuanced discussions and insightful conclusions. In this section, a comprehensive statistical analysis is presented, focusing on the evaluation of machine learning-based approaches for the classification of rice leaf diseases utilizing deep features.

It was observed that the DenseNet121 model demonstrated superior performance in classification via transfer learning. Consequently, in this subsection, particular attention was directed towards the deep features extracted from DenseNet121 for further in-depth analysis. These deep features were acquired from the fully connected layer of DenseNet and subsequently fed into the machine learning model for the classification task.

The results, outlined the test accuracy and time taken to complete prediction attained through the modification of densnets architecture. This comprehensive assessment serves as a critical benchmark, offering valuable insights into the efficacy and suitability of machine learning techniques in conjunction with deep features for accurate classification of rice leaf diseases. These findings hold significant implications for the development of robust and reliable diagnostic tools in the field of plant pathology.

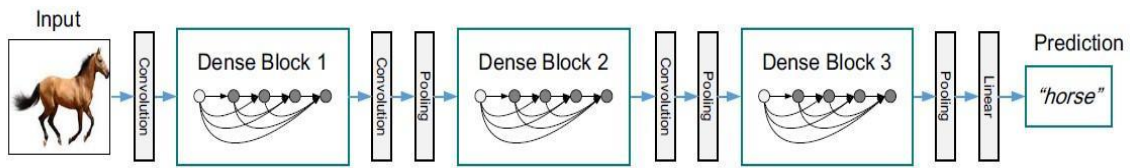


Fig. 4.1. DenseNet Blocks

4.1 DENSENET ARCHITECTURE

DENSENET 201 Layers	
Convolution	7×7 conv, stride 2
Pooling	3×3 max pool, stride 2
Dense Block (1)	6 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Transition Layer (1)	1×1 conv
	2×2 average pool, stride 2
Dense Block (2)	12 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Transition Layer (2)	1×1 conv
	2×2 average pool, stride 2
Dense Block (3)	48 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Transition Layer (3)	1×1 conv
	1×1 conv 2×2 average pool, stride 2
Dense Block (4)	32 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Classification Layer	7×7 global average pool
	1000D fully-connected, softmax

Fig. 4.2. Densnet201 architecture

MODIFIED DENSENET Layers	
Convolution	7×7 conv, stride 2
Pooling	3×3 max pool, stride 2
Dense Block (1)	6 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Transition Layer (1)	1×1 conv
	2×2 average pool, stride 2
Dense Block (2)	12 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Transition Layer (2)	1×1 conv
	2×2 average pool, stride 2
Dense Block (3)	48 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Transition Layer (3)	1×1 conv
	1×1 conv 2×2 average pool, stride 2
Dense Block (4)	31 cov layers of $[1 \times 1]$ & $[3 \times 3]$
Classification Layer	7×7 global average pool
	1000D fully-connected, softmax

Fig. 4.3. Modified Densnet Architecture

4.2 MODEL ACCURACY AND LOSS GRAPH

4.2.1 RESNET-50

ResNet-50 is a convolutional neural network (CNN) architecture widely used in computer vision tasks like image classification.

ResNet-50 Architecture

- ResNet-50 stands for Residual Network with 50 layers. It's a specific type of CNN architecture that addresses the vanishing gradient problem, a common hurdle in training deep neural networks.
- Residual connections: ResNet introduces "skip connections" that jump over some layers in the network. These connections add the input of a layer to the output of a later layer, allowing the network to learn from the gradients directly and train more effectively.
- Network depth: With these residual connections, ResNet-50 can achieve deeper architectures (50 layers) compared to traditional CNNs, enabling it to capture more complex image patterns.

Applications of ResNet-50

- Image classification: ResNet-50 excels at classifying images into predefined categories (e.g., identifying objects like cars, dogs, or furniture in pictures).
- Transfer learning: Due to its strong performance, ResNet-50 is often used as a pre-trained model for transfer learning. This means the initial layers, trained on a massive dataset like ImageNet, are used as a starting point for new tasks. The final layers are then fine-tuned on a smaller, specific dataset to achieve good results on new classification problems.

Benefits of ResNet-50

- Accuracy: ResNet-50 has achieved state-of-the-art performance on various image classification benchmarks.
- Efficiency: The residual connection approach helps alleviate vanishing gradients and allows for deeper networks, potentially improving model capabilities.

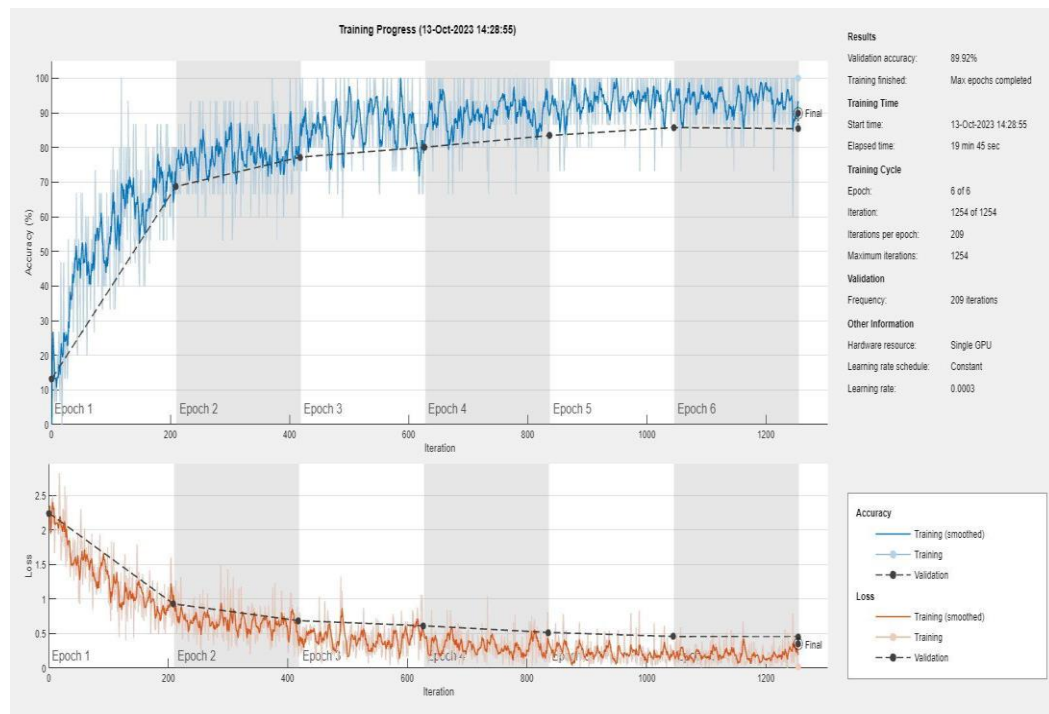


Fig. 4.4. ResNet-50 model graph

True Class	bacterial blight	220	5		7	4	1	1	1
	brown spot	7	425		30	2	10	2	6
	dead heart	3		413	3	1	1		
	downy mildew	1	1		296	3	3	2	4
	hispa	7	3		25	350	1	8	3
	leaf blast	3	12		29	9	397	5	14
	normal	2	4	4	6	18	4	440	4
	tungro	13	7		17	7	11	3	286
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig.4.5. ResNet-50 Confusion Matrix

4.2.2 ALEXNET

AlexNet, introduced in the 2012 paper "ImageNet Classification with Deep Convolutional Neural Networks" by Alex Krizhevsky et al., is a landmark convolutional neural network (CNN) architecture that significantly impacted the field of computer vision. Here's a breakdown for your report:

AlexNet Architecture

AlexNet marked a shift towards deeper CNNs, using eight stacked layers: five convolutional layers followed by three fully-connected layers. This depth allowed the network to learn increasingly complex features from images.

- **Convolutional layers:** These layers extract features from the input image using learnable filters. AlexNet employed rectified linear units (ReLUs) as the activation function in these layers, a novel approach at the time that improved training speed and performance compared to traditional activation functions.
- **Pooling layers:** Interspersed between convolutional layers were pooling layers, which downsample the feature maps to reduce computational cost and introduce some level of invariance to small image translations.
- **Fully-connected layers:** The final layers are fully-connected, meaning all neurons in one layer are connected to all neurons in the next. These layers take the high-level features learned by the convolutional layers and classify the image into a specific category.

Impact of AlexNet

- **Image Classification Breakthrough:** AlexNet achieved significant improvement on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a highly competitive benchmark for image classification. This success demonstrated the potential of deep learning for computer vision tasks.
- **Sparked Deep Learning Revolution:** AlexNet's performance inspired further research and development in deep learning.

architectures, paving the way for more advanced models like VGG16, ResNet, and others.

- Popularized Techniques: Key techniques introduced by AlexNet, like ReLUs and deeper architectures, became standard practices in CNN design.
- While revolutionary, AlexNet's architecture is computationally expensive compared to modern CNNs.
- You can mention the use of techniques like dropout (a regularization method to prevent overfitting) employed by AlexNet to improve generalization.
- Briefly compare AlexNet with its successors, highlighting how it laid the foundation for the advancements in CNN architectures.

By incorporating this information, you can effectively explain AlexNet's significance as a pioneering deep CNN architecture within your report.

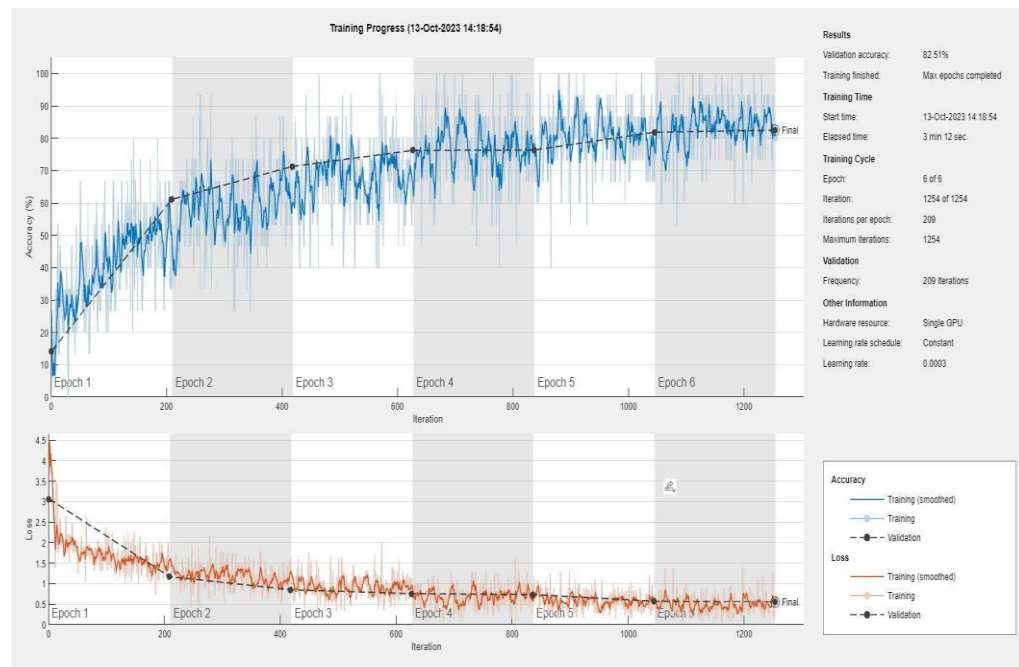


Fig. 4.6. AlexNet model graph

True Class	bacterial blight	173	20	5	4	20	5	8	4
	brown spot	2	444	1	3	12	13	6	1
	dead heart		2	404	2	7	3	3	
	downy mildew	1	20	3	249	16	5	9	7
	hispa	4	13	11	3	341	4	19	2
	leaf blast	1	40	8	18	23	367	4	8
	normal	2	10	7	1	42	8	409	3
	tungro	10	43	6	11	27	30	10	207
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig. 4.7. AlexNet Confusion Matrix

4.2.3 GOOGLNET

GoogleNet, also known as Inception v1, is a groundbreaking convolutional neural network (CNN) architecture introduced in the 2014 paper "Going Deeper with Convolutions" by Christian Szegedy et al. It achieved state-of-the-art performance on image classification tasks while promoting computational efficiency. Here's a breakdown for your report.

Architectural Innovation

- GoogleNet departs from the traditional stacked convolutional layer approach. It introduces Inception modules, which incorporate multiple paths within a single layer. These paths consist of:
 - 1x1 convolution: Reduces dimensionality for efficient processing.
 - 3x3 convolutions: Capture local spatial information.
 - 5x5 convolutions: Capture larger-scale features.
 - Pooling layer: Downsamples to reduce computational cost.
- The network combines the outputs of these paths, allowing it to learn diverse features at different scales within a single layer. This improves efficiency compared to stacking numerous traditional convolutional layers.

Additional Techniques

- Bottleneck layers: Utilize 1x1 convolutions within Inception modules to reduce dimensionality before applying 3x3 or 5x5 convolutions, further promoting efficiency.
- Grid Inception: A variant of Inception modules used later in the network, employing smaller filters (e.g., 1x7, 7x1) to capture features along different orientations.

Impact of GoogleNet

- Image Classification Champion: GoogleNet achieved impressive results on the ImageNet classification benchmark, surpassing previous models like AlexNet.
- Computational Efficiency: The use of Inception modules and bottleneck layers made GoogleNet more efficient than its predecessors, requiring fewer parameters and computations for similar or better performance.
- Influenced Future Architectures: GoogleNet's innovations, particularly Inception modules, inspired the development of subsequent CNN architectures like Inception v2, v3, and others.
- Briefly mention the limitations of GoogleNet, such as its slightly higher complexity compared to even more recent CNN architectures.
- You can discuss the use of global average pooling layers introduced by GoogleNet as an alternative to fully-connected layers for classification.
- Emphasize the trade-off between accuracy and efficiency achieved by GoogleNet's design, making it a significant milestone in CNN development.

By incorporating this explanation, you can effectively highlight GoogleNet's innovative architecture and its contribution to the advancement of CNNs in your report.

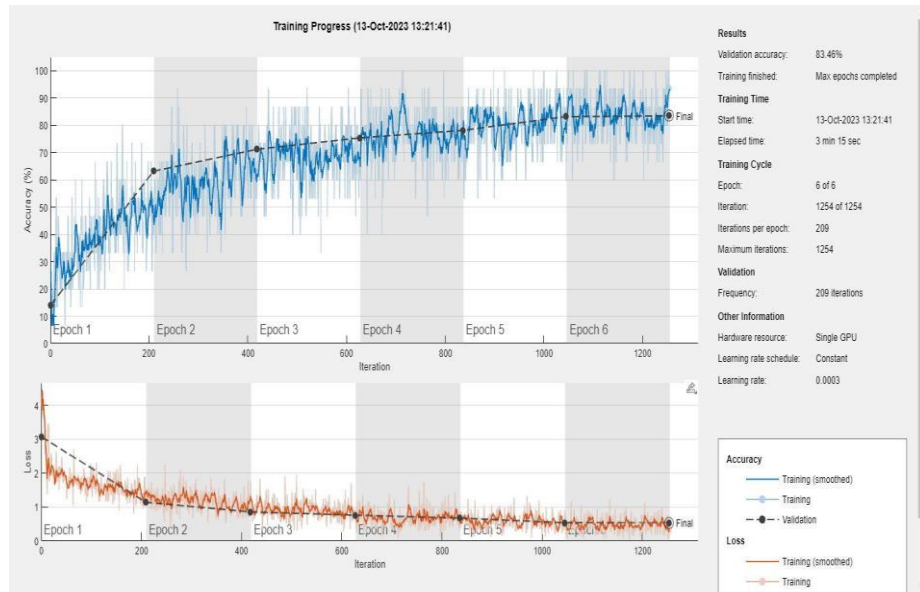


Fig. 4.8. GoogleNet model graph

True Class	bacterial blight	179	16	2	6	22	3	7	4
	brown spot	5	424	1	14	21	11	5	1
	dead heart		3	403	1	5	3	6	
	downy mildew	3	10	2	270	13	8	3	1
	hispa	5	8	6	10	337	3	28	
	leaf blast		26	4	26	26	373	9	5
	normal	2	4	6		32	8	429	1
	tungro	16	25	2	19	24	31	18	209
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig. 4.9. GoogleNet Confusion Matrix

4.2.4 RESNET-101

ResNet-101 is a convolutional neural network (CNN) architecture that builds upon the foundation laid by ResNet-50. It significantly improves image recognition

accuracy by increasing the network depth, while addressing the vanishing gradient problem that can hinder training in deep networks. Here's a breakdown for your report

ResNet Architecture Recap

- Briefly summarize the core concept of ResNet architectures, including the use of skip connections that bypass some layers in the network. These connections allow the gradients to flow more easily during training, enabling deeper networks to learn effectively.

ResNet-101 Details

- ResNet-101, as the name suggests, has 101 layers, significantly deeper than the 50 layers in ResNet-50. This increased depth allows the network to capture even more complex relationships within images, potentially leading to better image recognition performance.
- Bottleneck blocks: To maintain computational efficiency despite the deeper architecture, ResNet-101 utilizes bottleneck blocks. These blocks consist of 1x1 convolution layers before and after 3x3 convolutions, reducing the dimensionality of feature maps and minimizing computational cost.

Benefits of ResNet-101

- Improved Accuracy: Compared to ResNet-50, ResNet-101 often achieves superior performance on image classification tasks by leveraging its increased depth to learn more intricate image features.
- Transfer Learning: Similar to ResNet-50, the pre-trained weights of ResNet-101 can be effectively used for transfer learning. The initial layers, trained on a massive dataset like ImageNet, provide a strong foundation for various image recognition tasks when fine-tuned on a smaller, specific dataset.
- While ResNet-101 boasts higher accuracy, it comes at the cost of increased computational complexity compared to shallower networks like ResNet-50.

Discuss this trade-off depending on the specific application and resource constraints.

- Briefly mention other deep residual networks like ResNet-152, which push the depth even further, while acknowledging the potential for diminishing returns in accuracy gains with significant depth increases.
- You can compare ResNet-101 with other popular CNN architectures like VGG16 or Inception v3, highlighting the advantages of residual connections in addressing the vanishing gradient problem.

By incorporating this information, you can effectively explain ResNet-101's role in advancing CNN architectures and its strengths in image recognition tasks within your report.

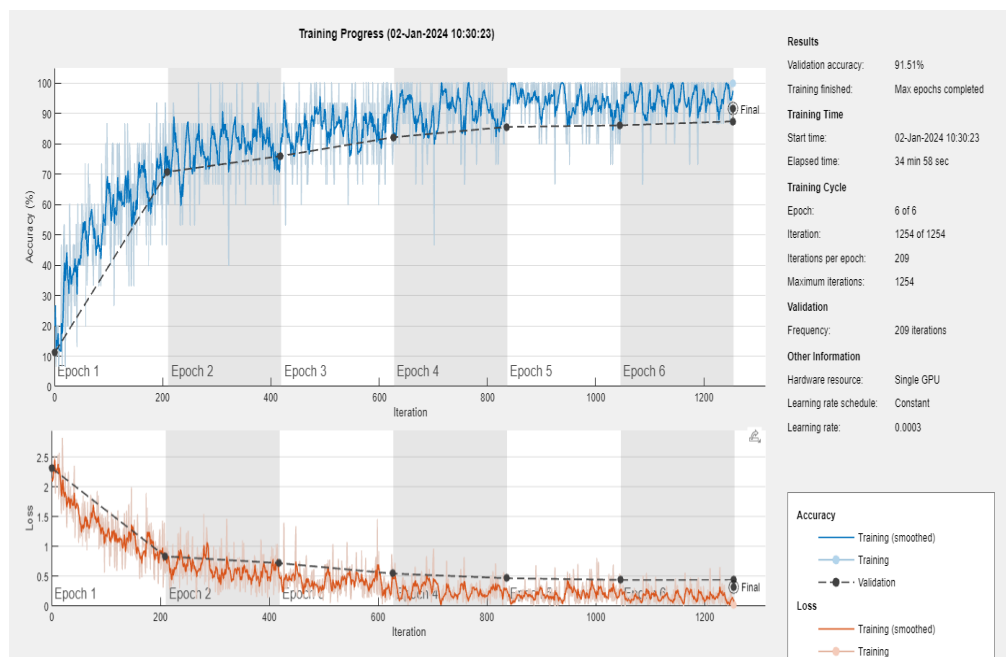


Fig. 4.10. Resnet-101 model graph

True Class	bacterial blight	222	3		4	4	4	1	1
	brown spot	4	445		18	3	9	1	2
	dead heart			420			1		
	downy mildew	1	6		284	3	6	1	9
	hispa	2	10	4	4	355	2	17	3
	leaf blast	7	7	2	16	17	396	3	21
	normal	1	3	6	2	11	1	454	4
	tungro	2	10	1	11	9	8	2	301
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig. 4.11. A Resnet-101 Confusion Matrix

4.2.5 XCEPTION

The Xception network is a convolutional neural network (CNN) architecture known for its depth and efficiency in image recognition tasks. Introduced by François Chollet in 2017, it takes inspiration from the successful Inception architecture but utilizes a distinct building block to achieve state-of-the-art performance. Here's a breakdown:

Building on Inception: Depthwise Separable Convolutions

- Briefly mention the Inception architecture, known for its use of inception modules with multiple filter sizes within a single layer. While powerful, Inception modules can be computationally expensive.
- Xception introduces depthwise separable convolutions as the core building block. This approach breaks down a traditional convolution into two separate steps:
- Depthwise convolution: Applies a single filter per input channel, extracting feature maps for each channel independently.

- Pointwise convolution (1x1 convolution): Applies 1x1 convolutions to reduce the number of channels in the output, introducing non-linearities and combining features.

Benefits of Depthwise Separable Convolutions

- Computational Efficiency: By separating depthwise and pointwise convolutions, Xception achieves similar feature extraction capabilities as Inception modules with significantly fewer parameters and lower computational cost. This makes it suitable for deployment on devices with limited resources.
- Maintain Feature Extraction Power: Despite the efficiency gains, depthwise separable convolutions can effectively capture spatial and channel-wise information within the image data.

Xception architecture

- Xception utilizes a similar approach to Inception, stacking multiple depthwise separable convolution blocks with different configurations. This allows the network to learn increasingly complex features from the input image.
- The network employs residual connections, similar to ResNet, to address the vanishing gradient problem and facilitate training deeper networks.

Impact of xception network

- State-of-the-Art Performance: Xception achieved competitive results on image classification benchmarks, demonstrating its effectiveness in image recognition tasks.
- Efficiency Advantage: Compared to Inception models with similar accuracy, Xception offers a significant advantage in terms of computational efficiency.

- Alternative for Resource-Constrained Environments: Xception provides a powerful alternative for deploying deep learning models on devices with limited processing power or memory.
- While efficient, Xception might not always outperform deeper Inception or ResNet architectures in terms of raw accuracy. Discuss this trade-off between efficiency and peak performance.
- Briefly mention pre-trained Xception models available for transfer learning, which can be a valuable starting point for various image recognition tasks.
- You can compare Xception with other CNN architectures, highlighting its strength in achieving good performance with a more lightweight and computationally friendly design.

By incorporating this explanation, you can effectively introduce the Xception network's design choices and its contribution to balancing efficiency and performance in deep learning for image recognition tasks within your report.

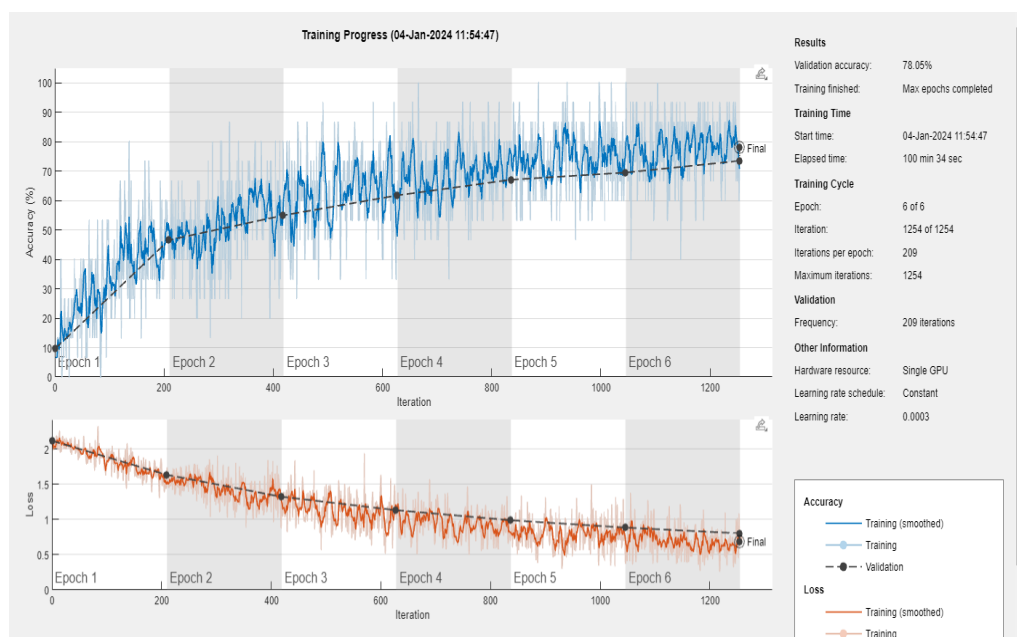


Fig. 4.12. Xception model graph

True Class	bacterial blight	146	15		18	25	12	4	19
	brown spot	16	358		21	20	28	12	27
	dead heart	1	4	408			5		3
	downy mildew	12	12	2	220	21	21	7	15
	hispa	9	14	9	7	309	13	31	5
	leaf blast	6	10	4	25	20	351	11	42
	normal		12	15	5	28	9	406	7
	tungro	17	10		21	20	11	9	256
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig. 4.13. Xception Confusion Matrix

4.2.6 NASNETMOBILE

NasNet-Mobile is a convolutional neural network (CNN) architecture specifically designed for **mobile and resource-constrained environments**. Developed by Google Brain in 2017, it leverages powerful neural architecture search (NAS) techniques to achieve high accuracy for image classification tasks while maintaining a compact and efficient design. Here's a breakdown for your report:

Key Features of NasNet-Mobile

- **Neural Architecture Search (NAS):** Unlike traditional CNNs where the architecture is hand-designed, NasNet-Mobile utilizes NAS to automatically discover an optimal network architecture. This allows the network to learn efficient building blocks that extract informative features from images.
- **Mobile-Friendly Design:** The NAS process prioritizes creating a CNN architecture with a low number of parameters and computations. This makes NasNet-Mobile suitable for running on smartphones, tablets, and other devices with limited processing power.
- **Strong Image Classification Performance:** Despite its compact size, NasNet-Mobile achieves competitive accuracy on image classification benchmarks, demonstrating its effectiveness in recognizing objects within images.

Benefits of NasNet-Mobile

- **Efficient Inference:** The small size and efficient design of NasNet-Mobile allow for fast image classification on mobile devices. This is crucial for real-time applications like object recognition in augmented reality or image search on smartphones.
- **Accurate on Limited Resources:** NasNet-Mobile can be deployed on devices with limited memory and processing power, making it a valuable tool for applications where traditional CNNs might be too resource-intensive.
- **Transfer Learning Potential:** Pre-trained NasNet-Mobile models can be used as a foundation for transfer learning tasks. By fine-tuning the pre-trained weights on a smaller, specific dataset, you can achieve good performance on new image recognition problems without requiring a massive amount of training data.
- While efficient, NasNet-Mobile may not achieve the same level of accuracy as larger, more complex CNN architectures on resource-rich environments. Discuss this trade-off between efficiency and peak performance.
- Briefly mention the publicly available pre-trained NasNet-Mobile models that can be leveraged for various computer vision tasks on mobile devices.
- You can compare NasNet-Mobile with other mobile-friendly CNN architectures, highlighting its strengths in achieving a good balance between accuracy and efficiency through the use of NAS.

By incorporating this information, you can effectively explain NasNet-Mobile's design choices and its advantages in bringing powerful image recognition capabilities to mobile devices within your report.



Fig. 4.14. NasNetMobile model graph

True Class	bacterial blight	151	26		10	23	15	10	4
	brown spot	1	388		13	24	32	15	9
	dead heart		5	395	1	4	2	11	3
	downy mildew	4	19	2	245	19	13	4	4
	hispa	6	21	1	5	322	11	30	1
	leaf blast		29		17	26	373	12	12
	normal	1	7	8	4	35	4	421	2
	tungro	7	30		13	24	26	17	227
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig. 4.15. NasNetMobile Confusion Matrix

4.2.7 DENSENET-201

DenseNet-201 is a convolutional neural network (CNN) architecture known for its **dense connectivity** and feature reuse capabilities. Introduced in the 2016 paper "Densely Connected Convolutional Networks" by Gao Huang et al., it achieves high accuracy on image classification tasks while promoting parameter efficiency compared to traditional CNNs. Here's a breakdown for your report:

Dense Connectivity for Enhanced Feature Propagation

- Unlike typical CNNs with isolated layers, DenseNet connects each layer to all subsequent layers in the network. This dense connectivity allows features extracted by earlier layers to be directly passed on as inputs to later layers.
- Feature Reuse: This approach encourages feature reuse throughout the network, as later layers can leverage the informative features learned by previous layers. It also alleviates the vanishing gradient problem, a common hurdle in training deep neural networks.

DenseNet-201 Architecture

- DenseNet-201, as the name suggests, has 201 layers. These layers are organized into dense blocks, where each layer receives the outputs of all preceding layers within the block as input.
- Growth Rate: DenseNets introduce a concept called the growth rate, which controls the number of feature channels added by each layer within a dense block. This helps regulate the model complexity and parameter efficiency.

Benefits of DenseNet-201

- Improved Accuracy: Dense connectivity promotes better feature propagation and reuse, leading to potentially higher accuracy on image classification tasks compared to traditional CNNs with a similar number of parameters.

- **Parameter Efficiency:** DenseNets can achieve good performance with fewer parameters compared to deeper networks with isolated layers. This translates to reduced memory usage and faster training times.

Applications of DenseNet-201

- **Image Classification:** DenseNet-201 is well-suited for classifying images into predefined categories, such as recognizing objects, animals, or scenes within pictures.
- **Transfer Learning:** Pre-trained DenseNet-201 models are available and can be used as a starting point for transfer learning tasks. This allows you to leverage the network's learned features for new image recognition problems on smaller datasets.
- While DenseNet-201 offers advantages, deeper DenseNets may require careful design to avoid overfitting due to the increased number of connections.
- Briefly mention the availability of pre-trained DenseNet-201 models for various deep learning frameworks like TensorFlow and PyTorch, making it easier to leverage its capabilities in projects.
- You can compare DenseNet-201 with other CNN architectures like ResNet, highlighting the strengths of dense connectivity in improving feature propagation and reducing parameter redundancy.

By incorporating this explanation, you can effectively introduce DenseNet-201's core concept and its contribution to CNN design for image recognition tasks within your report.

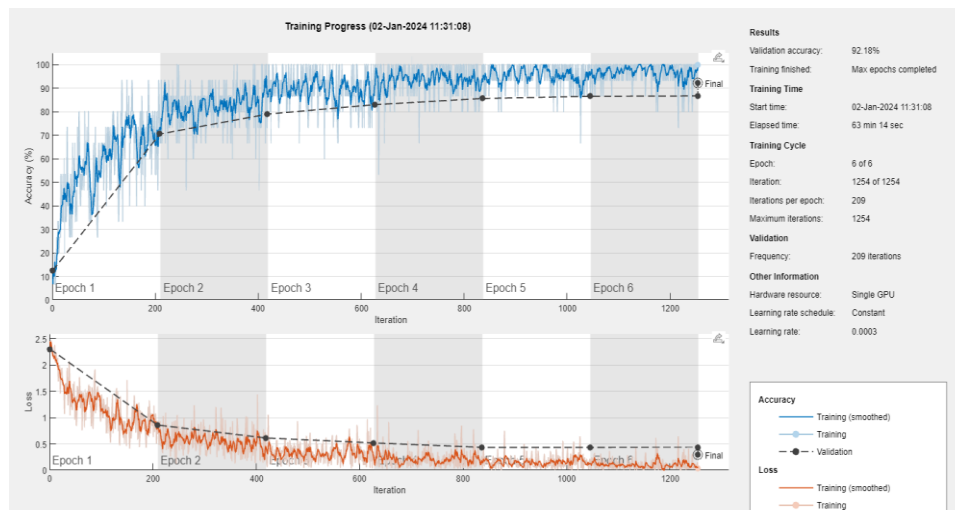


Fig. 4.16. DenseNet-201 model graph

True Class	bacterial blight	214	10			4	4	1	6
	brown spot	2	452		6	3	14		5
	dead heart			418			2		1
	downy mildew	1	8		279	1	11	2	8
	hispa	6	4	4	9	364	5	3	2
	leaf blast	9	5		11	7	417	1	19
	normal			4	2	18	7	445	6
	tungro	3	7		8	3	12	2	309
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig. 4.17. DenseNet-201 Confusion Matrix

4.3 MODIFIED DENSENET

Modified DenseNets are convolutional neural network (CNN) architectures that alter the original DenseNet architecture in various ways to achieve specific goals. While DenseNets themselves are powerful for image recognition, these modifications can improve performance, address limitations, or cater to specific applications. Here's a breakdown:

DenseNets and their Strengths

- Briefly summarize the core concept of DenseNets, including their dense connectivity between layers, which allows for better feature propagation and reuse compared to traditional CNNs. This approach can lead to improved accuracy and parameter efficiency.

Motivations for Modifications

- DenseNets, while effective, can have limitations. For instance, deeper DenseNets might be prone to overfitting due to the increased number of connections. Additionally, the architecture might not be optimal for all applications or resource constraints.
- Modified DenseNets address these limitations or introduce new functionalities by adapting the original DenseNet design.

Examples of DenseNet Modifications

- Reduced Depth DenseNets: These modifications aim to create shallower DenseNets while maintaining good performance. This can be achieved through techniques like removing dense blocks or using techniques like channel pruning to reduce the number of filters in each layer. This addresses concerns about overfitting and computational cost for resource-constrained environments.
- Attention Mechanisms: Some modifications incorporate attention mechanisms into DenseNets. These mechanisms focus on the most relevant parts of the input feature maps, potentially leading to better feature learning and classification accuracy.
- Hybrid DenseNets: These combine DenseNet blocks with elements from other CNN architectures like ResNets or Inception modules. This leverages

the strengths of different approaches to potentially achieve superior performance.

Benefits of Modified DenseNets

- Improved Performance: Specific modifications can target limitations of DenseNets, potentially leading to better accuracy on image recognition tasks.
- Addressing Limitations: Modifications can address issues like overfitting in deeper networks or cater to resource limitations by creating more efficient DenseNet variants.
- Increased Flexibility: The ability to modify the DenseNet architecture allows researchers and developers to tailor the network for specific applications or hardware constraints.
- Discuss the specific modifications being addressed in your report and their intended benefits.
- Mention how the modified DenseNet addresses limitations or leverages the strengths of the original DenseNet architecture.
- You can compare modified DenseNets with other approaches, highlighting their strengths in terms of addressing specific challenges or achieving better performance for certain tasks.
- By incorporating this information, you can effectively explain the concept of modified DenseNets, their motivations, and how they contribute to advancements in CNN architectures for image recognition tasks within your report.

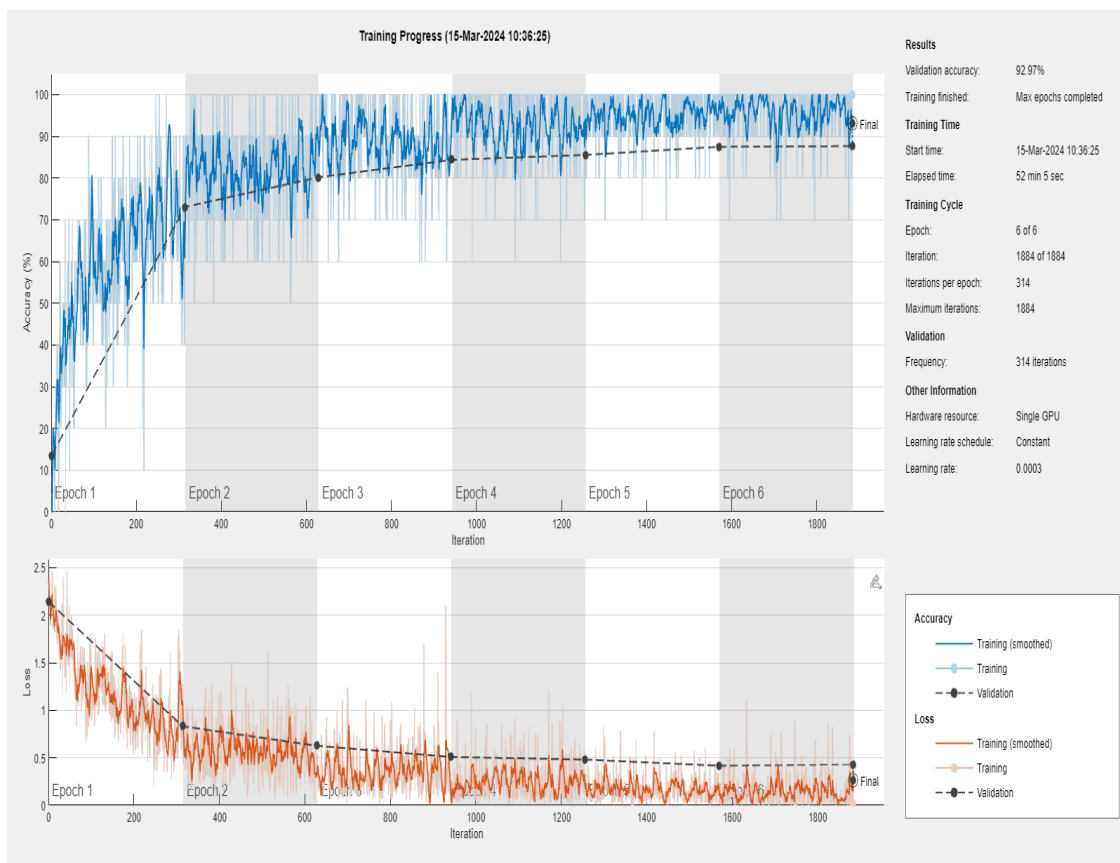


Fig. 4.18. Modified densenet model graph

True Class	bacterial blight	215	5		6	8	2	1	2
	brown spot	1	458		7	1	11		4
	dead heart			420	1				
	downy mildew	2	6		284	4	8	1	5
	hispa	2	4	4	7	356	4	18	2
	leaf blast	4	8		12	5	423	1	16
	normal	2	2	3	2	4	1	468	
	tungro	6	6		14	2	14	3	299
		Predicted Class							
		bacterial blight	brown spot	dead heart	downy mildew	hispa	leaf blast	normal	tungro

Fig. 4.19. Modified densenet Confusion Matrix

4.4 RESULT TABLE AND CHART

Classification models	Accuracy(%)
DenseNet 201	92.18%
GoogleNet	83.46%
ALexNet	82.51%
ResNet 50	89.92%
Nasnet Mobile	80.22%
ResNet 101	91.51%
Xception	78.05%
Modified Network	92.97%

Table 4.1. Networks result

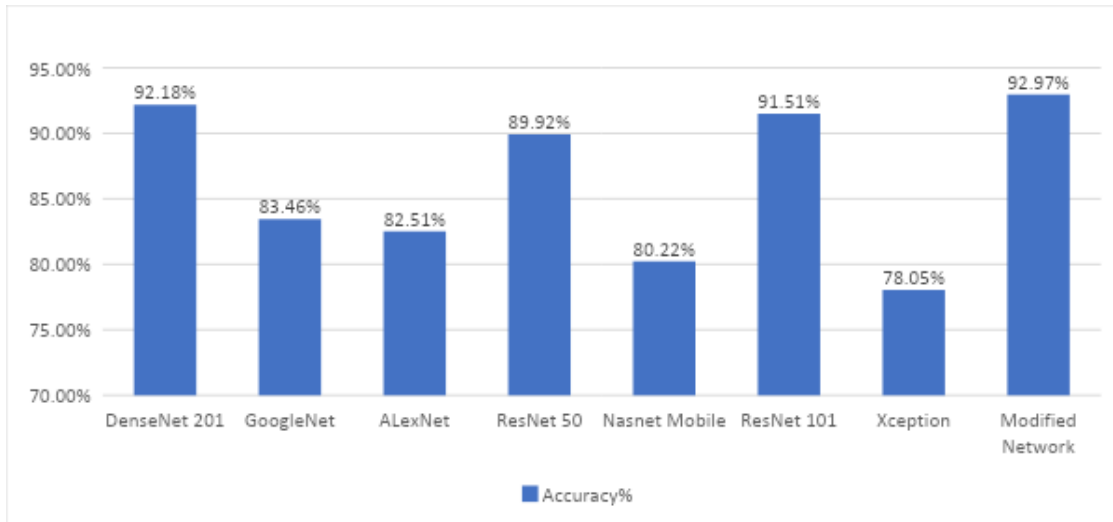


Fig. 4.20. Accuracy Chart

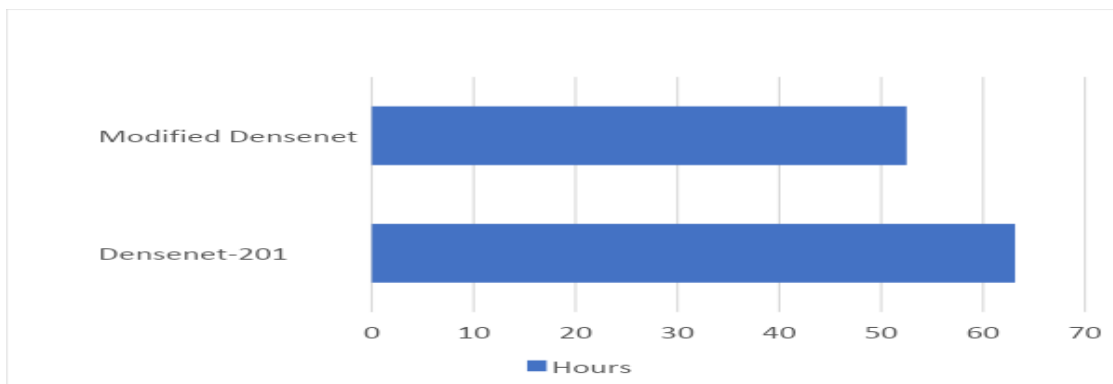


Fig. 4.21. Elapsed Time Chart

CHAPTER 5

CONCLUSION

In this study, a comparative analysis of various CNN algorithms, including DenseNet 201, GoogleNet, AlexNet, ResNet 50, NasNet Mobile, ResNet 101, Xception, and a modified network, was conducted for the identification of paddy crop diseases. The evaluation was based on accuracy performance

The findings indicate that DenseNet 201 and the Modified Network outperformed the other CNN algorithms in terms of accuracy for identifying paddy crop diseases. The modified network, which was customized through architectural adjustments, demonstrated the highest accuracy of 92.97%, showcasing the significance of optimizing network architectures for specific applications.

Overall, the study highlights the potential of CNN algorithms in the accurate identification of paddy crop diseases and emphasizes the importance of customizing network architectures to achieve improved performance. The results provide valuable insights for researchers and practitioners in the field of agricultural disease detection, paving the way for the development of more efficient and reliable disease identification systems to support sustainable crop management and enhance agricultural productivity.

This research explored a method for detecting crop diseases using powerful convolutional neural network (CNN) models. We investigated various architectures including DenseNet201, GoogleNet, AlexNet, ResNet-50, NasNet Mobile, ResNet-101, Xception, and even a modified DenseNet architecture. The study focused on identifying eight distinct disease classes: Bacterial Blight, Brown Spot, Dead Heart, Downy Mildew, Hispa, Leaf Blast, Tungro, and achieved impressive classification accuracies.

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