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A NOVEL TECHNIQUE PREDICTING THE RICE LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Various ailments affect rice, a staple crop in India, across different stages of its growth. Identification of these diseases manually poses a significant challenge, especially for farmers lacking in-depth knowledge. Recently, there's been promising advancement in deep learning research through automated picture identification systems employing Convolutional Neural Network (CNN) models. To tackle the scarcity of rice leaf disease image datasets, we developed a deep learning model using Transfer Learning on a limited dataset. Our approach leverages VGG-16 to train and evaluate the proposed CNN architecture, drawing from rice field and internet datasets. Impressively, the model achieves a 95 percent accuracy rate. Key terms in this study include Deep Learning, Convolutional Neural Network (CNN), fine-tuning, and rice leaf diseases.

Keywords: CNN, leaf disease, deep learning.

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1. GENERAL INTRODUCTION

Rice stands as a crucial nutritional cornerstone both in India and globally. Its growth journey is riddled with an array of afflictions. Ensuring top-notch crop quality hinges on swift identification and treatment of these diseases. Yet, the challenge looms large due to the expansive lands managed by individual farmers, the diverse spectrum of diseases they contend with, and the potential for multiple diseases within a single crop. Finding agricultural experts in remote regions proves arduous and time-intensive. Hence, the need arises for Automated Systems. Artificial neural networks (ANNs) and support vector machines (SVMs) havebeen employed in research endeavors to aid farmers and enhance the accuracy of plant illness identification. However, the efficacy of these systems heavily relies on the chosen features. The advent of convolutional neural networks allows image recognition without the need for extensive picture preprocessing and facilitates inherent feature selection. Nonetheless, acquiring extensive datasets for such challenges proves exceedingly challenging. In instances where dataset sizes remain modest, leveraging a model trained on a larger dataset becomes preferable. Developing anew model via Transfer Learning offers the flexibility to either remove the final layer of connections or fine-tune these concluding layers to Page 1 and align more precisely with the specific dataset at hand. Farmers can capture photos of affected leaves using their smartphones and transmit them to our server. Our neural network processes these images, accurately diagnosing the illness and offering treatment recommendations promptly to the farmers. This innovation stemmed from the ubiquitous presence of cell phones. The paper presents a disease classification module within an automated system. Our work harnesses the power of convolutional neural networks, enabling the development of a robust deep learning technique. To adapt the VGG-16 model to our specific datasets, Transfer Learning was instrumental in fine-tuning the fully connected layers. Subsequently, we conducted an in-depth analysis of our errors, striving to comprehend their root causes.

1.1 Problem Statement

Plant diseases wield a significant impact on the agricultural sector, severely affecting crop productivity and causing substantial losses for farmers. Early disease detection is pivotal to enhance the quality, quantity, and overall productivity of yields while minimizing pesticide use and mitigating environmental damage. This research aimed to detect and categorize diseases present in rice leaves, encompassing four classes:

1.2 Objectives

a) To collect the dataset of normal and disease rice

b) To train and test the dataset of rice healthy, his pa, brown spot, and leaf blast. The project employed convolutional neural networks for feature extraction from rice images. Additionally, machine learning classifiers such as Random Forest and K-Nearest Neighbors were utilized for disease classification within these categories. The initial CNN model demonstrated strong performance in feature extraction, potentially leading to increased accuracy.

c) To apply the convolutional neural network for classification of rice diseases

d) To detect the disease form the rice using CNN

2. LITERATURE SURVEY

Numerous studies have focused onidentifying and categorizing plant diseases, particularly in the realm of recognizing rice leaf ailments [23]. In reference [2], a framework centered on CNN architecture is devised for distinguishing between three distinct rice diseases and healthy images, while [10] employs a CNN-based model for detecting diverse plant leaf diseases. Additionally, [6] implements principal component analysis (PCA) to eliminate redundant information and generate a reduced-dimensional vector for each rice leaf disease image. Furthermore, a range of classifiers were employed to assess performance, ultimately revealing SVM as the top performer in recognizing rice leaf diseases. In reference [29], the diagnosis of plant disease via CNN involves extracting learned features through perturbation, gradient, and reference-based visualization techniques using InceptionV3. Utilizing the mixed layer aids in generating profound features encompassing shape and color diversity, allowing for the removal of 75% of parameters while maintaining accuracy and minimizing loss. On the other hand, reference [16] demonstrates the superior effectiveness of CNN-based models compared to traditional feature extractors like LBPH and Haar WT specifically in identifying rice blast disease. Furthermore, the researchers in [28] explored several state-of-the-art CNN architectures such as Alex Net [14], Google Net [27], and Le Net [15] for detecting ten different diseases affecting Tomato leaves, concluding that Le Net exhibited the highest accuracy among them.

Reference [11] highlights the enhanced accuracy achieved in plant leaf disease recognition through the implementation of the Google Net architecture. In [19], a transfer learning model leveraging state-of-the-art CNN models like Alex Net and Google Net is developed for the detection of plant diseases. Utilizing the Caffe Net deep learning framework from the Berkley Vision and Learning Center, [7] focuses on CNN training for plant disease recognition [26]. Meanwhile, [17] delves into a comparative analysis of diverse pooling strategies such as mean-pooling, max-pooling, and stochastic pooling and applies gradient descent algorithms to train CNNs specifically for identifying rice leaf diseases. Furthermore, in [12], texture features are computed using a color co-occurrence matrix, followed by the application of Naïve Bayes for the classification of plant diseases based on leaf characteristics. In reference [13], the utilization of two pre-trained deep models- VGG16 [25] and Caffe Alex Net- enables the extraction of features from selected fruit crop diseases. These discerned features play a pivotal role in disease classification employing multi-class SVM. On the other hand, [22] delves into the refinement and application of two cutting-edge CNN architectures, namely VGG16 and InceptionV3, alongside a two-stage CNN model tailored for identifying rice diseases and pests. Notably, the authors identify the two-stage CNN model as particularly effective for devices constrained by memory limitations. Furthermore, in [21], the Resnet-34 architecture is harnessed through transfer learning techniques, complemented by the use of cyclical learning rates (CLR) for the precise classification of rice plant diseases.

A significant hurdle in effectively identifying rice or plant leaf diseases lies in addressing the challenges posed by diverse image-capturing conditions and backgrounds. These conditions notably constrain model performance; for instance, certain existing works are constrained to plain backgrounds [4, 9, 19, 26, 30] and struggle with various image capturing conditions [16]. Additionally, optimizing the parameters of large-scale networks in models designed for plant leaf disease recognition relies heavily on state-of-the-art- art CNN architectures. However, despite the superior recognition rates achieved by these architectures, their extensive network parameters pose challenges for deployment on memory-restricted devices. Ultimately, some CNN-based models aimed at recognizing rice leaf diseases encounter limitations in generalization [9]. To address these challenges, we introduce a pioneering CNN-based model composed ofconvolution and pooling layers, coupled with adense layer and a softmax layer, tailored specifically for the identification of rice leaf diseases. Our custom-designed CNN model focuses on minimizing network parameters. We've curated a distinctive dataset encompassing diverse image backgrounds and varying image capturing conditions, augmenting it to bolster our model's generalization capabilities. To validate the efficacy and superiority of our model, rigorous testing is conducted using an independent set of rice leaf disease images.

Atila *et al.*'s (2021) study concentrated on plant leaf disease classification employing the Efficient Net Deep Learning Model. Recognizing the limitations of certain classic Machine Learning algorithms, this work leveraged the Efficient Net deep learning approach for superior disease classification. The study involved a comparison of this model's performance against other deep learning models, employing the Plant Village database. The training incorporated both an original database comprising 55,448 photographs and an augmented dataset with 61,486 images. Transfer learning techniques were employed for training the Efficient Net model and other deep learning architectures. Notably, within the Efficient Net framework, the B4 and B5 models showcased commendable performance. Specifically, on the augmented dataset, the B4 model exhibited precision and accuracy values of 99.39 percent and 99.97 percent, respectively. The B5 model has an accuracy of 99.91 percent and a precision value of 98.42 percent.

In the study by Sujatha *et al.* (2021), the comparative effectiveness of Deep Learning versus Machine Learning methodologies in identifying plant leaf diseases is explored. Diseases have the potential to afflict plants at any stage of their life cycle, leading to diminished crop yield and reduced market value. Hence, within the agricultural domain, disease identification holds paramount importance. This investigationencompasses the development and assessment of various Machine Learning and Deep Learning techniques for disease detection in citrus plants. Methods such as Support Vector Machine,

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Random Forest, Stochastic Gradient Descent, Inception-v3, VGG-16, and VGG-19 were trained specifically for citrus plant disease diagnosis. The superior performance of Deep Learning approaches over Machine Learning methods resulted in notably high categorization accuracy. The model performances were as follows: VGG-19: 87.4 percent, Inception-v3: 89 percent, VGG-16: 89.5 percent, RF: 76.8 percent, SGD: 86.5 percent, SVM: 87 percent. Notably, RF exhibited the lowest accuracy among the methods assessed, while VGG-16 emerged as the most accurate classifier.

In Hu *et al.*'s study (2021), the focus was on detecting and analyzing the severity of tea fungal diseases using deep learning methodologies. Initial attempts using machine learning-based image processing techniques for tea leaf blight detection yielded subpar and inaccurate results. Consequently, this research pivoted towards employing deep learning methods to enhance disease classification precision. The incorporation of the Retinex algorithm served to enhance original image quality by mitigating light fluctuations and shadows. To bolster the detection capabilities for obscured, occluded, and smaller leaf segments, a Faster Region-based Convolutional Neural Networks model was implemented. Notably, the utilization of the VGG16-trained network yielded the most promising outcomes. Overall, the findings from this deep learning approach showcased superior performance when juxtaposed with conventional machine learning algorithms, as per the study's report.

Numerous studies have leaned on classical classifiers, where outcomes are closely tied to the chosen feature selection methods, and image preprocessing holds pivotal significance in the research process. Recognizing the high recognition accuracy offered by CNNs, recent studies have increasingly turned to this technology. For instance, a paper titled "Detection of Plant Diseases using CNN" employed a training dataset comprising 87,848 photos from 25 plant species categorized into 58 groups, encompassing instances of "healthy" plant growth. Notably, one of the top-performing models achieved an impressive 99.53% success rate in accurately classifying objects. However, during evaluation on a distinct dataset sourced from real-world scenarios-comprising 54,306 photos across 14 crop types, each exhibiting 26 different illnesses alongside healthy the initial 99.35% success rate plummeted drastically to 31.4%. The challenges in determining the severity of a condition extend beyond mere classification due to heightened intra-class similarities across images within the same category, intensifying thecomplexity of identification.

A convolutional neural network (CNN) was employed for rice disease detection, trained on a dataset containing 227 images of both healthy and diseased rice plants. The classifier, utilizing AlexNet, demonstrated an impressive capability of accurately discerning unhealthy plants with a precision rate of 91.23%. To further the study, the authors curated an additional dataset comprising 500 images representing ten distinct rice leaf and stem illnesses. Drawing inspiration from Le-Net and AlexNet, they devised a novel architecture andsubjected it to testing, achieving a notable accuracy rate of 95.48%. Given the sparse nature of the data, preprocessing steps such as image resizing to 512x512, normalization, PCA, and whitening were conducted. Notably, instead of employing max pooling, they opted for stochastic pooling, asserting its effectiveness in preventing overfitting.

3. EXPERIMENTAL SETUP

The experiment utilized a 64-bit Windows 10 system, employing the Keras 2.2.4 deep learning framework with a Tensor flow 1.14.0 backend and Python 3.7.2 to construct the CNN model.

3.1 Processing of Images

Furthermore, alongside field-captured images, the dataset comprises online-acquired images showcasing leaf blasts, leaf blight, brown spots, and healthy plants. Utilizing the Image Data Generator in Keras, diverse enhancement methods such as zoom, rotation, and horizontal/vertical shifts were applied to the collected photos, resulting in the generation of new images at a 224x224 pixel resolution.

3.2 CNN's Modeling School

Loading the picture dataset is essential for conducting both training and testing phases. For training purposes, the class labels and images are segregated into separate arrays. Employing the train-test split technique, 70% of the data is allocated for training, while the remaining 30% is designated for testing. Within this split, 30% of the data serves for validation, and the subsequent division allocates 70% for further use. To encode the class labels as integers, a one-hot encoding procedure is implemented, representing each label as a vector instead of an integer. Additionally, in Keras, the final fully connected layers are removed, allowing for the addition of untrainable components to the system. In conclusion, before applying the softmax filter, we implemented it on the flattened output of the feature extractor. Our model, crafted entirely from scratch, utilized the Adam optimizer and categorical cross-entropy as the classification loss function. We halted the training at 25 epochs as the results showed consistent stability. Figure-3 outlines the steps involved in the classification process undertaken in this study. Justification for the chosen model will be provided to substantiate its selection.

The concept known as "transfer learning" involves applying knowledge gained in one context to another. As real-world scenarios often lack abundant labeled data, transfer learning proves highly advantageous for training neural network models. Training a neural network from the ground up necessitates substantial data, which may not always be accessible. Leveraging a pre-trained model allows for the construction of a robust machine-learning model using minimal training data. In our case, we utilized a pre-trained VGG Net tailored to our limited dataset,

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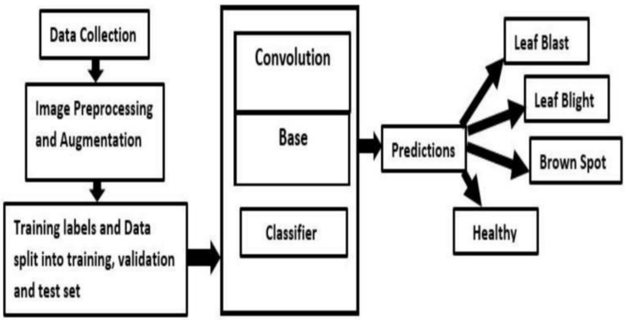

Figure-1. Overview of the steps of the proposed model.

4. CONVOLUTIONAL NEURAL NETWORK ALGORITHM

This study proposes the utilization of Convolutional Neural Networks (CNN) as a deep learning approach to automate governmental functions via Artificial Intelligence technology. Individuals access news and notifications concerning new government programs online, offering them the opportunity to express their opinions regarding these initiatives. Leveraging this information can significantly aid governmental decision-making processes. To achieve automated identification of public sentiment towards these schemes, software resembling human cognition is essential. This software must discern whether the expressed opinions lean towards positivity ornegativity.

The proposed approach by the author involves constructing a CNN model designed to emulate human brain functionality, aiming to create an automated system for detecting opinions. This CNN model, intended for autonomous decision-making without human intervention, holds the potential for implementation across various services. The author's conceptualization of multiple models includes one for recognizing handwritten digits and another for discerning sentiments from textual feedback on government initiatives, presenting an existing technique. As an extension, our study incorporates a novel model capable of detecting emotions from facial images. Utilizing facial expressions as indicators of emotions surpasses the limitations of words or sentences in conveying feelings, enabling our research to predict people's emotions based on their facial cues.

To elucidate the functioning of a convolutional neural network in image classification, we'll create a concise six-layerneural network capable of distinguishing between different images. Designing a compact network is essential for CPU compatibility. Training a conventional neural network on a standard CPU demands significantly more parameters and time. Nonetheless, our objective revolves around showcasing the construction of a practical convolutional neural network using TensorFlow.

The essence of neural networks lies in mathematical models tailored for optimizing solutions. Neurons serve as fundamental computation units within these networks. When an input (let's say, x) is inputted into an active neuron, computations occur (like multiplication with a variable, w, and addition of another, b), resulting ina new value (e.g., z = wx + b). The ultimate output of a neuron, termed activation, is produced using a non-linear activation function denoted as f. These activation functions vary in shape and type, among which the sigmoid function is prominent. Neurons are labeled based on their activation roles, with a variety of options available, such as RELU and TanH.

This progression in neural networks involves the aggregation of neurons into a structure termed a "layer" when they're arranged in a sequence. Refer to the illustration below for a visual depiction of these layered elements within the network.

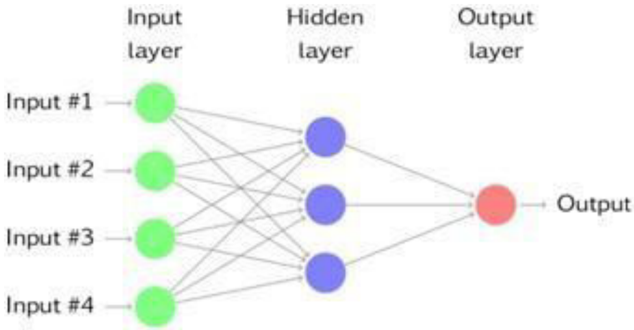

Figure-2. Convolutional neural network Software Environment.

5. DEEP NEURAL NETWORKS

Deep learning also referred to as "deep structured learning," constitutes a subset within the expansive realm of machine learning methodologies. Its applications span various modes of learning, including supervised, semi-unsupervised, and unsupervised paradigms. Acrossdiverse domains such as computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug development, and medical image analysis, a wide array of deep learning architectures, including convolutional neural networks and recurrent neural networks,have found practical application.

Artificial neural networks (ANNs) were constructed drawing inspiration from the distributed communication and information processing observed in biological systems. However, distinctions exist between artificial neural networks (ANNs) and biological brains. Unlike the dynamic and analog (plastic) nature of most organic animal brains, artificial neural networks are static and symbolic in theirfunctioning.

Within deep learning architectures, the network comprises multiple hierarchical levels. Early research indicated that non-polynomial activation functions, when coupled with a single hidden layer of unbounded breadth, could serve as universal classifiers. A recent advancement, involving an infinite number of bounded-size layers, presents a practical and optimally implementable version while upholding theoretical universality under reasonable conditions. These layers within deep learning, albeit heterogeneous, diverge from biologically-informed connectionist models due to this structured organizational aspect.

SCREENSHOTS

To run project install python 3.7 and tensorflow package 1.14.0 and then install Django==2.1.7

After installation run below command from 'RiceDisease' folder

Python manage.py runserver

Then open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below screen

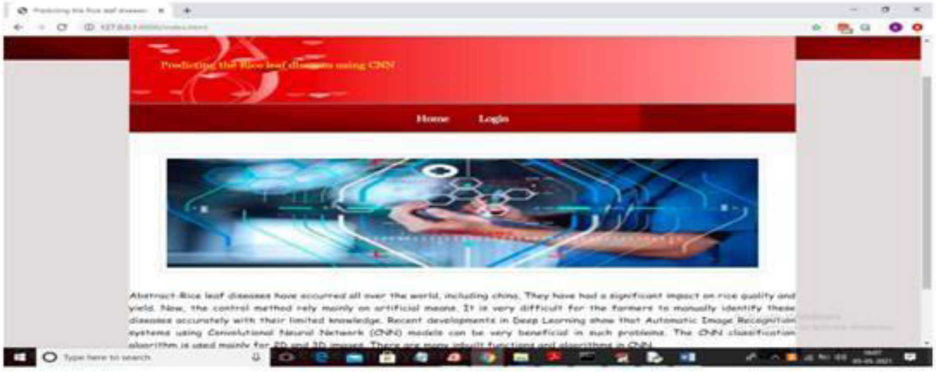

Figure-3. Login link.

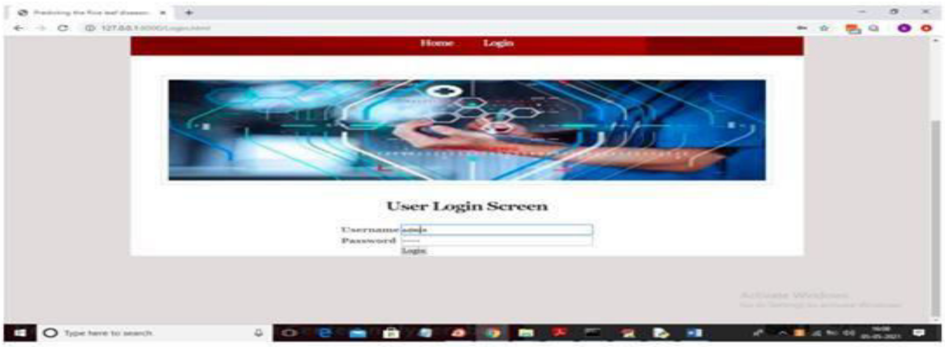

Figure-4. User name and password image.

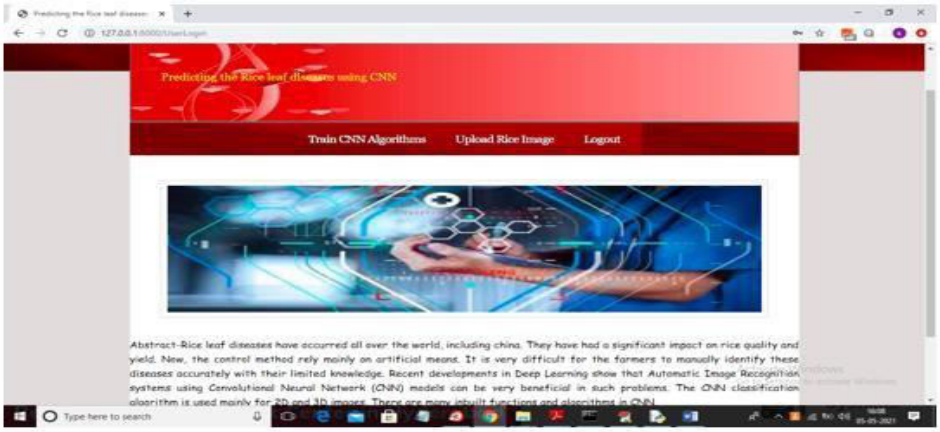

Figure-5. Select CNN Algorithm.

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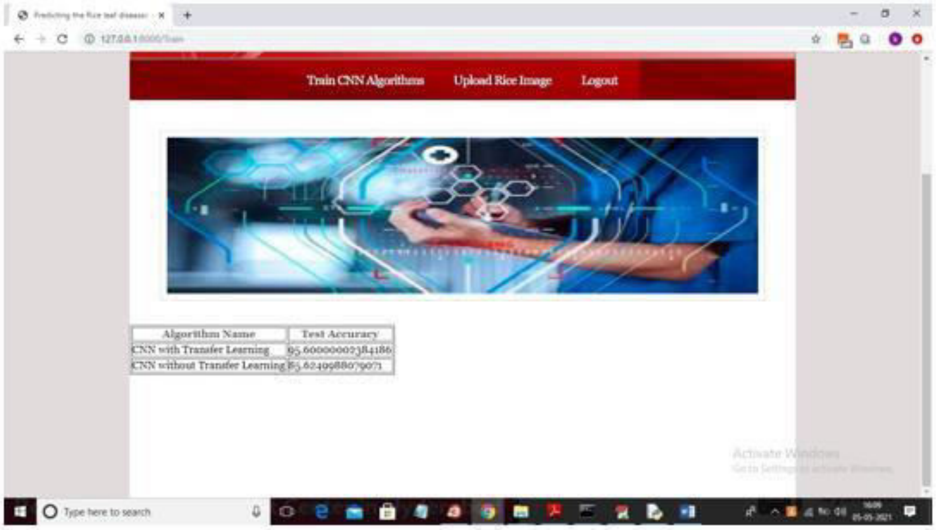

Figure-6. Train CNN algorithm with transferlearning.

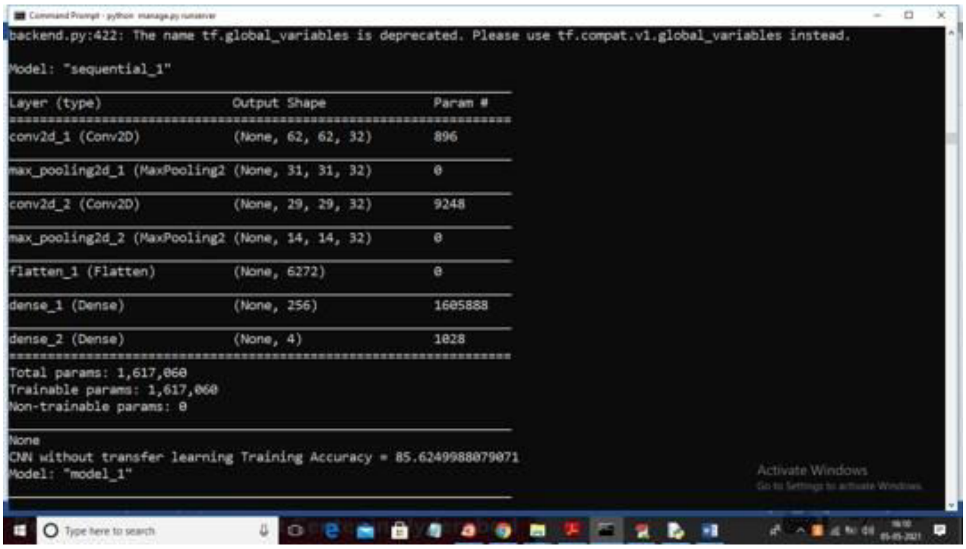

Figure-7. Normal CNN is created by fourlayers.

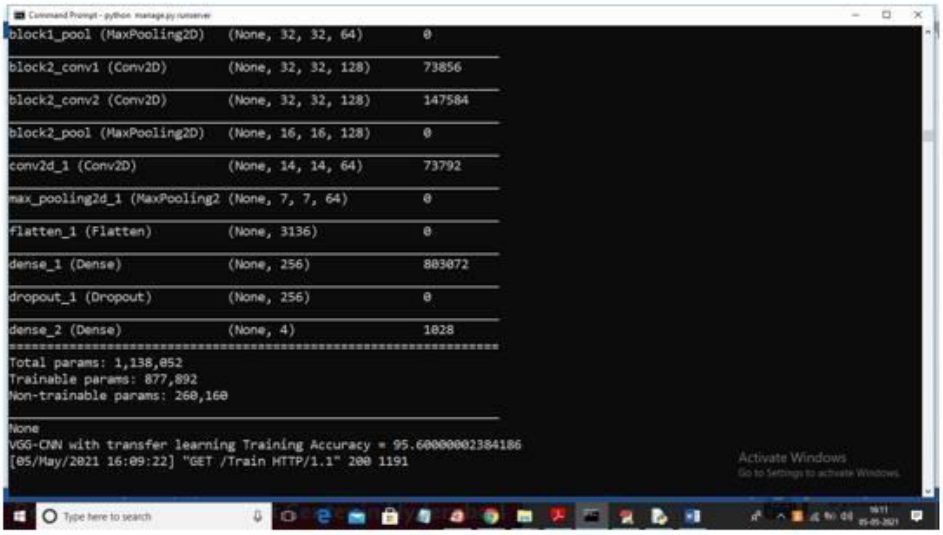

Figure-8. VGG-16 with layers.

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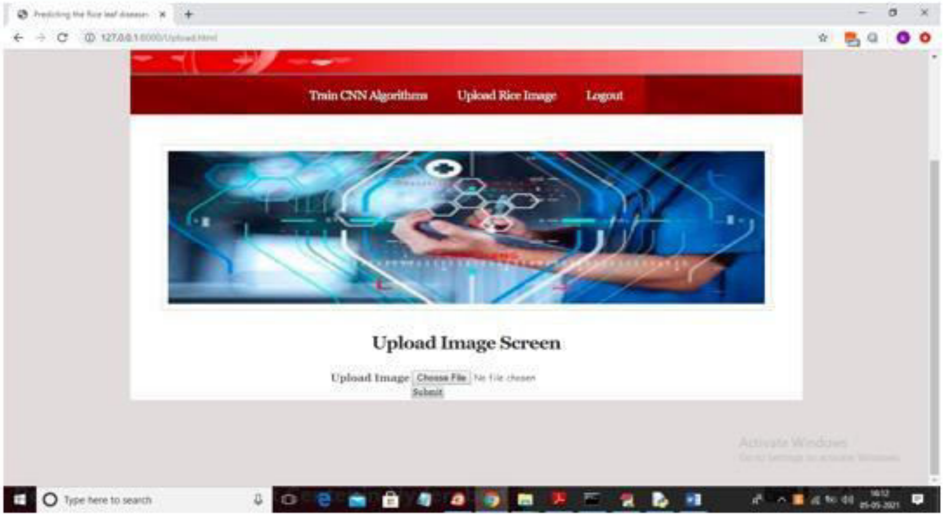

Figure-9. Upload and test image.

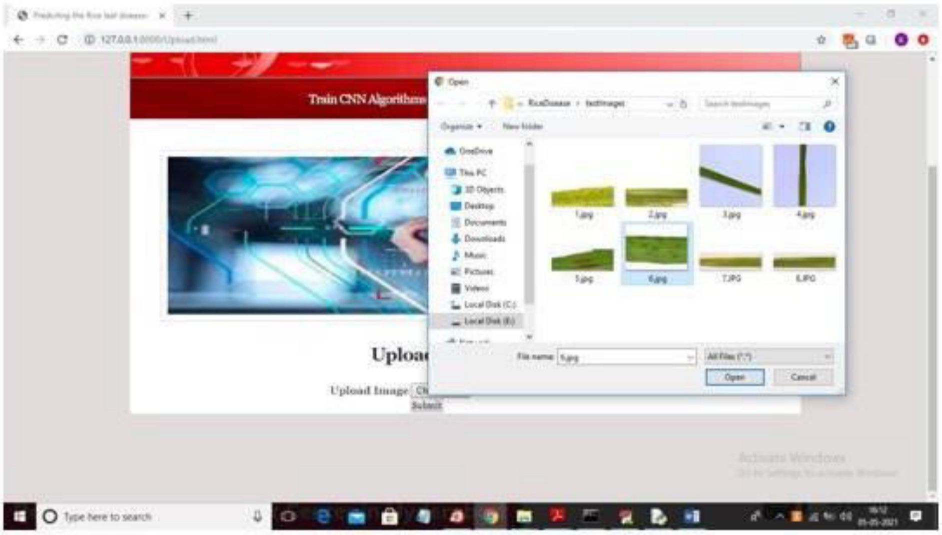

Figure-10. Uploading JPEimagesge from thedatabase.

Figure-11. Uploaded disease image.

Figure-12. Predicted and healthy issues.

6. RESULTS AND DISCUSSIONS

A. Calculations

The proposed model exhibited an accuracy of 97% on the training data and 95% on the test data following 20 epochs of training using a dataset of 150 samples. A separate CNN model, devoid of transfer learning, underwent training and testing on the same dataset but with varied split ratios. Despite fine-tuning optimization settings involving batch sizes, epochs, and the rms prop optimizer, the maximum accuracy attained stood at74% across batch sizes of 16, 30, and 0.4 epochs, respectively. In this CNN model without transfer learning, ReLU, Maxpooling, and dropout layers precede two Fully Connected Layers and SoftMax.

Figure-4 within Table-I presents a comparative analysis between suggested CNN models with and without Transfer Learning. Additionally, Figure 5 illustrates the training and validation accuracy of the CNN utilizing Transfer Learning across different epochs. This showcases the performance and comparison between CNN models with and without transfer learning.

Table-1.

Model	Test Accuracy
CNN with transferlearning	92.46%
CNN without transferlearning	74%

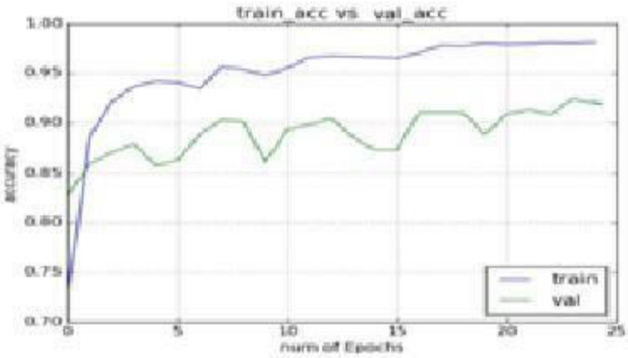

Figure-13. Plot of accuracy versus Epochs.

B. Error Analysis

Within Figure 6, the proposed CNN model inaccurately categorizes images (a)-(f), leading to misclassifications for various disease types detailed below. Image (a), despite being related to Rice Blast, is incorrectly assigned to Brown Spot. Blurriness and pixelation in the image, coupled with small brown patches on the same rice leaf, might have caused this error.2. Images (d) and (e), labeled as "Healthy," actually depict leaf blight, potentially due to poor lighting and image blurring, leading to misrepresentation.3. Image (f), labeled as Brown Spot, actually showcases a healthy leaf. However, its poor contrast and blurriness resulted in this mislabeling.4. Images (b) and (c) correctly belong to Brown Spot but are classified as Blast by the EPA. This discrepancy might be due to small blast lesions resembling brown spot lesions.5. In image (d), the blast lesions are misconstrued as brown spot lesions, leading to misclassification.

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Figure-14. From left to right (a)-(f) rice disease images that are misclassified by the model rice blast image (b)and (c) brown spot (d) and (e) Leaf Blight (f) healthy.

7. CONCLUSIONS

In this study, our introduced deep learning architecture demonstrated an accuracy of 95% in correctly classifying test photos. The model was trained using 40 photographs of rice leaves and tested on an additional set of 20 images, showcasing its efficiency. Through fine-tuning the

VGG16 model, we significantly improved the model's performance despite the limited dataset.To ensure optimal training, we limited the maximum epochs to 20, as further data indicated no enhancement in accuracy or reduction in loss across both the training and validation sets.

REFERENCES

[1] T. Gupta. 2017. Plant leaf disease analysis using image processing technique with modified SVM- CS classifier. Int. J. Eng. Manag. Technol. (5): 11-17.

[2] Y. Es-saady, T. El Massi, M. El Yassa, D. Mammass and A. Benazoun. 2016. Automatic recognition of plant leaves diseases based on a serial combination of two SVM classifiers. International Conference on Electrical and Information Technologies (ICEIT). pp. 561-566.

[3] P. B. Padol and A. A. Yadav. 2016. SVM classifier-based grape leaf disease detection. Conference on Advances in Signal Processing (CASP). pp. 175-179.

[4] L. Liu and G. Zhou. 2009. Extraction of the rice leaf disease image based on BP neural network. International Conference on Computational Intelligence and Software Engineering. pp. 1-3.

[5] S. Arivazhagan and S. V. Ligi. 2008. Mango Leaf Diseases Identification Using Convolutional Neural Network. International Journal of Pure and Applied Mathematics. 120(6): 11067-11079.

[6] B. Liu, Y. Zhang, D. He, and Y. Li. 2012. Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks Symmetry. X. X. & Suen, C. Y. A novel hybrid CNN-SVM classifier for recognizing handwritten digits. Pattern Recognition. 45: 1318-1325.

[7] Y. Lu, S. Yi, N. Zeng, Y. Liu and Y. Zhang. 2017. Identification of Rice Diseases Using Deep Convolutional Neural Networks. Neurocomputing. 267, pp. 378-384.

[8] R. R. Atole, D. Park. 2018. A Multiclass Deep Convolutional Neural Network Classifier for Detection of Common Rice Plant Anomalies. International Journal of Advanced Computer Science and Applications. 9(1): 67-70.

[9] V. Singh, A. Misra. 2017. Detection of Plant Leaf Diseases Using Image Segmentation and Soft Computing Techniques. Information Processing in Agriculture. 4(1): 41-49.