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CNN BASED PLANT DISEASE DETECTION WITH TRANSFER LEARNING

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ABSTRACT: Agriculture is essential for the economy and plant leaf diseases must be minimized. Early recognition of problems is important, but the manual inspection is slow, error-prone, and has high man power and time requirements. Artificial Intelligence can be used to extract leaf colour, shape or texture data. Thus aiding the detection of infections. Crop is one of the major cultivation in India which is affected by various diseases at various stages of its cultivation. It is very difficult for the farmers to manually identify these diseases accurately with their limited knowledge. Recent developments in Deep Learning show that automatic image recognition systems using Convolutional Neural Network(CNN) with Transfer Learning(TL) models can be very beneficial in such problems. Since Rice leaf disease image dataset is not easily available.

1. INTRODUCTION

Agriculture plays a crucial role in sustaining human life and global economies by providing food, raw materials, and employment opportunities. However, one of the major challenges faced by the agricultural sector is the prevalence of plant diseases, which can lead to significant losses in crop yield and quality. If left undetected or untreated, plant diseases can spread rapidly, causing devastating effects on food security and economic stability. Traditional methods of plant disease detection primarily rely on visual inspection by farmers or agricultural experts, which can be time-consuming, labor-intensive, and prone to human errors. Moreover, these methods may not be effective in identifying early-stage infections, leading to delayed intervention and increased damage.

With rapid advancements in technology, machine learning (ML) and deep learning (DL) techniques have gained significant attention for their ability to provide automated, accurate, and efficient solutions for disease detection in plants. Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image-based classification tasks, including plant disease identification. CNNs can automatically extract features from plant images, recognizing patterns associated with different diseases with minimal human intervention. However, training CNN models from scratch requires a large dataset of labeled images and extensive computational resources, which may not always be available in agricultural applications.

Wheat is a major crop and a major source of sustenance for humans all over the globe. It is the second-largest planted crop, ranking fourth among the 20 most important agricultural crops. The Global wheat production in the year 2020-21 was 772 million metric tons, and the yield it produces is critical to the food security of the majority of the world's population. There are a number of fungal and nutrient deficient diseases that may impact wheat production, including leaf-rust, nitrogen deficiency, powdery mildew, Septoria, stem rust, etc. This disease causes a reduction in crop production, and it is a global problem. There is no more than a 20% damage that is caused by the causal agents of the aforementioned diseases, which can be treated by the timely application of fungicides. However, the consequences of leaf-rust and stem-rust, which cause nearly 30% damage (depending upon region and season), are significant economically. The most efficient strategy to combat these illnesses is their prevention and prompt deployment of preventative measures. However, such a method is hard to implement without a prompt and accurate pathogen detection system. This thesis focuses on automatically detecting diseases and pathological parts present within the wheat leaf images using advanced machine learning and computer vision algorithms. The major demand of the world in agriculture is the extraordinary production; therefore, most of the countries utilize new advanced technologies for increasing the productivity of agriculture products. The advanced technologies must satisfy the food production rate.

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Nevertheless, the other factors such as abiotic stress factors (e.g. insects, pathogens, drought stress or nutrition deficiencies and weed) and several classes of pests mostly affect the Wheat plants at any stages. Thus, the quality and quantity of agriculture products are slightly affected (Mahlein et al. 2012). Therefore, the detection of plant disease is must, but, it also difficult and challenging. This necessitates close monitoring of the paddy leaf to analyse its condition for disease infection. Both post-harvest yield and production are mainly affected by the diseases. Previously, the severity of disease in the plant is analysed only by visual inspection (naked eye observation) techniques. The accuracy of this analysis mostly depends upon the experience and knowledge of the analyser. The time taken for visual inspection is high, due to the large cultivation area and it needs constant human observations. Therefore, a mechanism is required to replace the manual analysis. Image processing techniques are used for such purposes in agriculture to detect the type and intensity of disease affected in the Wheat plants (Patil and Kumar 2011).

2. LITERATURE SURVEY

This chapter presents a literature survey of the existing state-of-the-art methods for wheat plant disease classification approaches. Further, to ensure the comprehensive coverage of the relevant literature, this chapter is divided into different subsections. Agriculture is the livelihood of many countries. Various environmental factors affect the yield of agriculture by causing severe diseases in Wheat plants. Wheat crop is the staple food for most of the Asian countries and the diseases that affect this crop are not much detected by farmers due to their lack of knowledge. The modifications or interruptions in the normal functioning of Wheat plants are caused by diseases. Both the cultivated and the wild plant species are affected by the diseases. The causative agents of plant diseases are due to certain environmental conditions, affected pathogens, and seasonal causes etc., which are influenced in accordance with the plant varieties. The infections of diseases are mainly caused due to the agents of nematodes, viruses, bacteria and fungi. Due to the attack of various pests and the diseases, at different phases of crop growth, certain threats are really faced by the farmers. This is because, the unpredictable cyclic change of climatic conditions and the new trends of the modern society tend to operate against nature. The overall spreading velocity and the severity of diseases are determined by the capability of crops to withstand the infections.

The wheat crop suffers from the various type of diseases such as Wheat stem rust, stripe rust, leaf rust, septoria tritici blotch (Mycosphaerella graminicola or Septoria tritici), nodorum blotch, tan spot, fusarium head blight (wheat scab or ear blight), spot blotch, helminthosporium leaf blight, wheat blast, et cetera. The most common disease of the wheat crop is Wheat rust, which significantly reduces the wheat crop yields. The Wheat rust disease can be further categorized as Stem rust, Stripe rust, and Leaf rust. Wheat leaf rust is the widely outspread and common rust disease among all three. All these diseases make the leaf dry, thus affecting the photosynthesis process. In this direction, several researchers have reported their studies to identify wheat plant diseases using automatic machine learning algorithms. Mainly this work focuses on identifying different levels of FHB infection in winter wheat using differential and ratio combinations of Sentinel-2 bands and digital mapping images at a regional scale. This experiment produced an accuracy of 84% for REHBI, OSAVI, and RDVI, contained accuracy of 74%, and user’s accuracy of 89%. This system attains an accuracy of 95%. In the agriculture domain, the other ontology technique is applied in work. This study uses the linked data approach in order to apply near real-time activities using the semantic web. Another noteworthy contribution by suggested a mobile app for automatic detection and localization of plant diseases using an image dataset (WDD2017). The author has employed VGG-FCN-VD16 and VGGFCNS deep learning approaches and achieved an accuracy of 95.12% and 97.95%, respectively. Another similar approach adopted in used a combination CNN and AleXNet models to automatically identify wheat leave diseases. The proposed method achieved an accuracy of 84.54% for predicting the correct class.

The symptoms of diseases in the wheat plant, since its beginning stages are noted from certain variations such as colour, growth, shape and size of the Wheat crops. Some commonly seen symptoms are dot and dark spot which appears in the leaves and other parts of the plant and abnormal root region bulging. From these specified symptoms, the infections are diagnosed in the early stage of disease and it helps to protect the crops from complete damage. Due to drastic increase in population, there is a huge demand for more crop yield. The property of an infectious agent is to reproduce high on its host and to propagate from one leaf to another.

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Likewise, the other conditions such as deficiency of essential mineral, disadvantageous relationships between oxygen and moisture, toxic constituents in the atmosphere or soil, excess of temperature can affect the leaves of the Wheat plants. The reproducing capability of non-infectious causal agents is compared with infection agents (**Barbedo et al. 2016)**. Every year, about 50,000 new-born diseases are survived in the world that disturbs the normal attitudes of plant behaviour. Hence, it is necessary to control such effective.

Wheat crops (Oryza sativa L.) acts as one of the staple food and the supreme cereal crop for around half the population of the world. India is considered as the largest Wheat harvesting country in the world, and the Wheat farming field was reported as 44.1 million hectares. As per the percent population of the world, need for increased level of Wheat production (**Harsonowati et al. 2017**). In both African and Asian countries, enormous amount of Wheat is consumed because of its economic growth and the population rate. Thus, it seems that the overall economy of the state directly depends on the productivity level of wheat **Mohanty et al (2019).** In the current scenario, diseases are the main cause that affect plant growth. For example, in Odisha, the overall available farm land 1.10 lakh acres were affected by the brown plant hopper disease in a single year.

Too et al. (2019) Conducted a comparative analysis of multiple CNN architectures, including AlexNet, VGG16, InceptionV3, DenseNet, and ResNet50, for plant disease classification. The study found that ResNet50 consistently outperformed other models in terms of classification accuracy, robustness, and computational efficiency. The residual connections in ResNet50 helped address the vanishing gradient problem, allowing for deeper feature extraction and improved performance in recognizing plant diseases. The study concluded that ResNet50 was a strong candidate for real-world plant disease detection applications due to its high accuracy and scalability.

Kamal et al. (2022) Implemented a MobileNet-based transfer learning approach for lightweight and real-time plant disease detection on mobile devices. The study emphasized the importance of deploying AI models in low-resource environments, making them accessible to farmers in remote areas. MobileNet was chosen for its efficiency in reducing computational complexity while maintaining high accuracy. The researchers fine-tuned the MobileNet model using a plant disease dataset and optimized it for mobile applications, achieving high classification accuracy with minimal inference time. The model was integrated into a mobile application that allowed farmers to capture leaf images using smartphone cameras and receive instant disease diagnoses. The study demonstrated that MobileNet, when combined with transfer learning, can enable scalable, cost-effective, and real-time plant disease detection in field conditions, significantly benefiting precision agriculture.

3. PROPOSED METHOD

Agriculture is a critical sector that supports the global population by providing food, raw materials, and economic stability.

However, Plant diseases are a significant threat to global food security, causing substantial crop losses and economic damage. Early detection and identification of plant diseases are crucial for preventing the spread of disease, reducing crop losses, and promoting sustainable agriculture.

The primary objective is to segregate the diseased wheat leaves from healthy leaves using different image processing and machine learning techniques. Secondarily, identification of different abnormalities to timely diagnose and take preventive measures to improve crop production. Initially, we applied bound box segmentation, combined color and texture feature extraction, and benchmark supervised classification algorithms to assess the classification performance. Subsequently, we proposed binary gray wolf optimization (BGWO) based ensemble classification approach for multiclass classification of wheat leaves disease.

In the current scenario, the farmers used their naked eyes to identify the different plant diseases, which need continuous monitoring and expertise. This method is highly **Time-consuming** and **Expensive**, which is very difficult to execute for large-scale farming. Thus, to eliminate this problem**, Machine Learning**-based classification techniques that are **CNN** with **Transfer learning** have been proposed for identifying wheat plant diseases. This proposed model has the capability to identify and classify both nitrogen deficiency and leaf rust.

4. STEPS

Here's a breakdown of the process:

i. **Capture Image:** A camera captures an image of a plant leaf.

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ii. **Image Preprocess:** The captured image undergoes preprocessing**.**
iii. **Convolutional Neural Network (CNN):** The preprocessed image is fed into a CNN, a type of deep learning algorithm particularly effective in image recognition. The CNN extracts relevant features from the image.
iv. **Training Images:** The CNN is trained on a dataset of labeled images of both healthy and diseased plant leaves. This training process allows the network to learn the distinguishing features of different diseases.
v. **Testing Image:** A separate "testing image" of a plant leaf, potentially with disease, is input into the trained CNN.
vi. **Leaf Disease Detection:** The CNN identifies and classifies any diseases present in the testing image.

5. BENEFITS

- **Improved Accuracy:** CNNs excel at feature extraction from images, making them highly effective at recognizing complex patterns associated with plant diseases. Transfer learning leverages pre-trained models, enhancing detection accuracy even with smaller datasets.
- **Faster Model Training**: Transfer learning saves time by reusing pre-trained models (such as VGG16, ResNet, etc.), allowing fine-tuning instead of starting training from scratch. This significantly reduces the computational burden and time required.
- **Reduced Need for Large Dataset:** Collecting vast amounts of labeled plant disease data can be resource-intensive. Transfer learning enables CNNs to perform well with limited labeled data, as they build on pre-learned features from large general datasets**.**
- **Generalization Across Plant Species:** Pre-trained models can generalize across different species of plants, making them adaptable to a wide variety of crops and diseases, improving scalability.
- **Early Disease Detection:**Using CNNs to detect diseases early can help in managing plant health before problems spread, leading to better crop yields and less pesticide usage.
- **Real-Time Detection:** CNNs, when integrated into mobile apps or drones, can offer real-time disease detection in the field, which is essential for precision agriculture.
- **Cost-Effective:** By reducing the need for manual inspection, expert intervention, and extensive data collection, CNN-based disease detection systems reduce operational costs for farmers and agricultural companies.
- **Automation and Efficiency:** Automation of disease identification and management decisions increases efficiency by reducing the time and labor involved in manual inspections. This can help in large-scale farming operations.
- **Scalable to Multiple Disease Types:** Transfer learning allows fine-tuning to adapt to various diseases on different crops, enabling a system to detect a wide range of plant diseases across different regions.
- **Integration with IoT and Precision Agriculture:** CNN-based plant disease detection can be integrated with IoT devices like sensors and drones. This allows for continuous monitoring of crops and the collection of data that can be used for more precise, data-driven farming decisions.

6. RESULTS

Fig: Brown spot

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Fig: Bacterial Blight

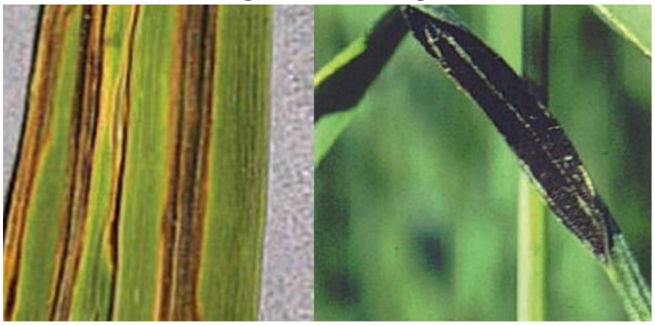

Fig: Leaf Rust

7. CONCLUSION AND FUTURE SCOPE

This chapter summarizes the thesis' major contributions and highlights the numerous achievements related to the objectives set up in the introductory chapter. Further, the thesis outcomes are described in Section 2. In conclusion, we will discuss the different contributions and potential future study areas that have been opened up as a result of the work presented in this thesis.

Summary of the Contributions:

we have made the following research contributions in this thesis: (i) developed an automatic disease diagnosis method that utilizes wheat leaf image data and machine learning algorithms to accurately classify the diseases; (ii) improved the efficiency and effectiveness of the diagnosis of the diseases using segmented image data; (iii) investigated efficient feature extraction and selection technique that can select the optimal feature to encode the disease patterns; (iv) proposed optimized ensemble classification approach to leverage the advantages of multiple learners; (v) compared the performance of the proposed approaches with the existing state of the art methods. As a result, we may conclude that all of the goals of this thesis have been met. In addition, the following section describes the individual contributions made by each target in more detail:

Objective I:

To study and develop automatic disease diagnosis methods that utilize wheat leaf image data and machine learning algorithms to classify the diseases accurately.

Objective-I aims to develop an automatic wheat plant disease identification and classification method that can accurately identify the diseases and assist the farmers and experts in timely employing preventive measures to improve crop productivity. To achieve this objective, we investigated the existing state-of-the-art methods, and based on the literature survey, the most pervasively used feature extraction methods are employed to encode the disease patterns. The extracted features are further passed to the supervised machine learning algorithms to segregate them into healthy and diseased images. This type of automated system can also be integrated into android based mobile devices to serve the purpose in remote areas where the experts are not available or very few in number. **Objective II**:

To identify the concepts to improve the efficiency and effectiveness of the diagnosis of disease using segmented image data.

The aim of Objective-II is to study the concept to improve the efficiency of the diagnostic procedure. The input wheat leaf images consist of a large non-contributing background regions, which substantially impact feature extraction and overall classification performance. To address this, segmentation is performed using the bounding box method. The method detects the pixels (black pixels in this case) in the background region and generates a

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new bounding box image by eliminating the background. The segmented images are now used for further processing, which improves the detection performance and significantly reduces the computation requirements.

Objective III:

To investigate efficient feature extraction and selection techniques that can select the optimal feature to encode the disease patterns.

The aim of Objective-III is to investigate the features that can efficiently encode the disease texture and color intensity variations. To achieve this, we evaluated different color and texture features and combinations of them. The experimental results show that the first-order statistical feature, gray level co-occurrence matrix feature, color moments, HSV histogram, and histogram of oriented gradients features are extracted and combined. Further, the combined feature is very large in size; therefore, to minimize the effect of the curse of dimensionality, we employed the binary gray wolf optimization technique. The method selects the strongest features for the classification task, which improves the classification performance.

Objective IV:

To study and develop a classification ensemble approach to leverage the advantages of multiple learners.

The Objective-IV aimed to develop an optimized ensemble approach, which performs comprehensive learning of the input features. The method creates numerous meta learners and one base learning algorithm. The input feature vectors are used to train the meta learner, and the decision from each learner is passed to the base learner, which performs the aggregated decision. The main advantages of using an ensemble approach are that, unlike single learner based algorithms that suffer from statistical, computational, and representational issues [29], the ensemble approach improves poor learners and creates a more generalized model with greater prediction performance. The obtained results reveal that the proposed ensemble approach significantly improves the detection performance.

Objective V:

To compare the performance of the proposed approaches with the existing state-of-the-art methods.

The aim of Objective-V is to compare the performance of the proposed approaches with the existing state-of-the-art methods. The comparative results reveal that the proposed method outperformed the other approaches.

The future scope of CNN-based plant disease detection, significantly boosted by transfer learning, promises increasingly accurate, robust, and early diagnosis capabilities deployable in real-time through mobile apps, drones, and edge computing devices. Leveraging advanced transfer learning strategies, alongside techniques like federated learning and synthetic data generation, will help overcome data scarcity and diversity challenges. Future systems will likely integrate visual data with other sensor inputs (like hyper spectral or thermal imaging) for a more comprehensive plant health assessment. This technology is poised to move beyond simple detection towards quantifying disease severity, predicting yield loss, and seamlessly integrating with precision agriculture platforms for automated decision support and targeted interventions, ultimately contributing to more sustainable farming practices and enhanced global food security.

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