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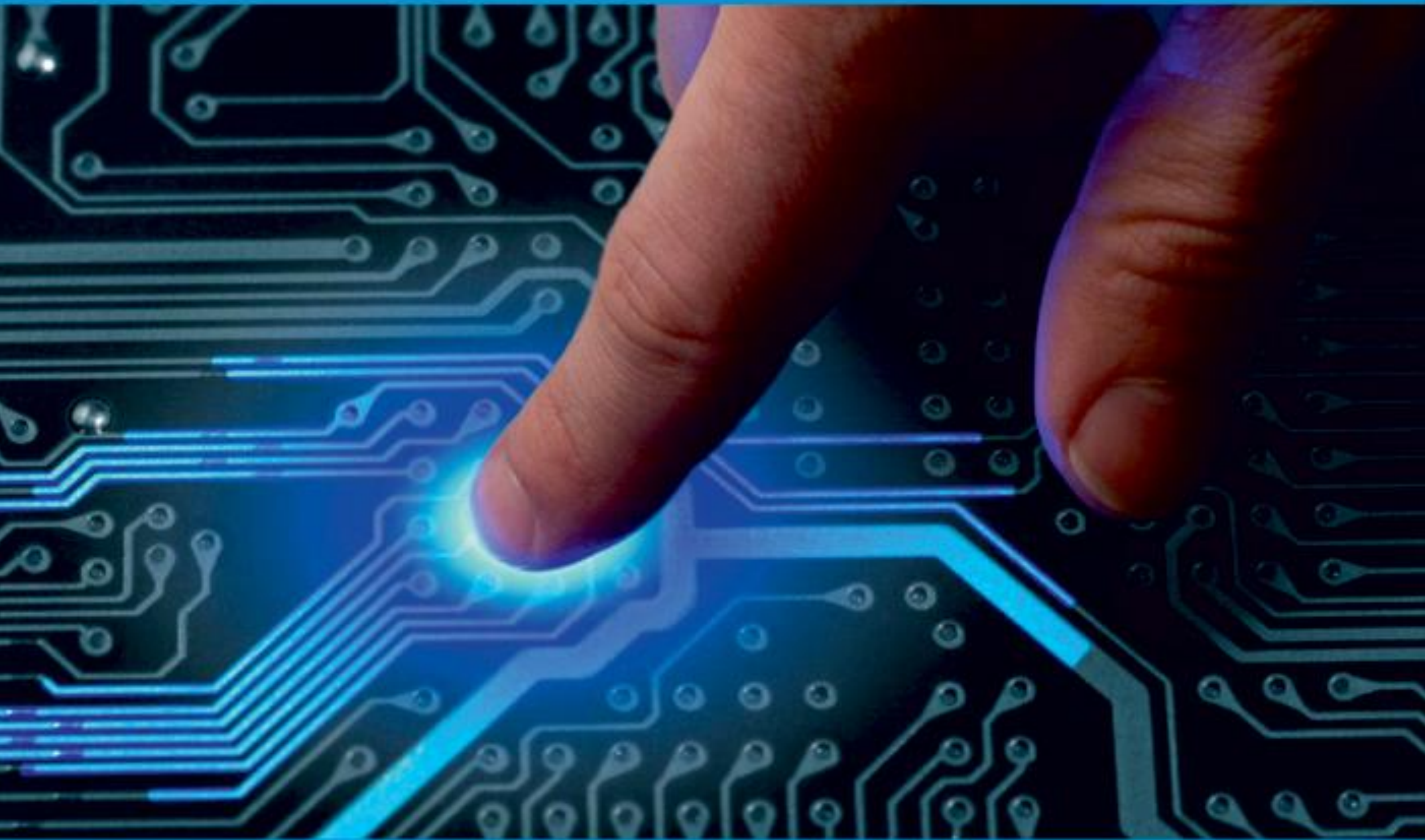

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Automated Wheat Disease Diagnosis Using Deep Learning

Shifa Banu, Maseerah Fathima, Mohammed Faraz Mukaram, Mohammed Junaid,

Mrs Jyothi M Patel

Student, Department of CSE, ATME College of Engineering, Bannur Rd, Mysuru, India

Assistant Professor, Department of CSE, ATME College of Engineering, Bannur Rd, Mysuru, India

ABSTRACT: This venture presents an inventive approach to wheat edit administration through the integration of profound learning and picture acknowledgment strategies. Utilizing a convolutional neural arrange (CNN) demonstrate prepared on assorted datasets of solid and infected wheat plant pictures, our framework offers real-time conclusion of common wheat maladies counting Brown Rust, Septoria, Yellow Rust, Stripe Rust, and Crown Root Decay. By analyzing pictures captured from webcams, our framework gives precise infection distinguishing proof and offers personalized proposals for preventive measures and safeguards to relieve edit harm. This innovation presents a promising arrangement to enable agriculturists with proficient instruments for checking and keeping up the wellbeing and efficiency of their wheat crops.

The usage of profound learning calculations permits for the computerized and quick discovery of wheat infections, essentially diminishing the time exertion required for manual assessment. Besides, the CNN model's capacity to memorize from a endless sum of information empowers it to generalize well and adjust to distinctive natural conditions, guaranteeing vigorous execution in different agrarian settings. Through nonstop checking and examination of edit pictures, agriculturists can expeditiously recognize infection flare-ups and take opportune activity to avoid advance.

I. INTRODUCTION

Our extend presents an imaginative approach to wheat edit administration by coordination profound learning and picture acknowledgment methods. At its center could be a convolutional neural organize (CNN) demonstrate prepared on differing datasets of solid and ailing wheat plant pictures, empowering real-time conclusion of common wheat illnesses like Brown Rust, Septoria, Yellow Rust, Stripe Rust, and Crown Root Decay. By analyzing pictures captured from webcams introduced in areas, our framework offers exact infection recognizable proof and personalized proposals for preventive measures and safety measures to moderate edit harm.

The system's user-friendly interface encourages consistent interaction, permitting agriculturists to effectively transfer pictures for examination and get significant bits of knowledge. Leveraging the control of profound learning, our demonstrate forms pictures rapidly, providing ranchers with convenient data to create educated choices around malady administration. Furthermore, the system's integration with webcams empowers persistent checking of wheat crops, guaranteeing early discovery of illnesses and proactive intercession to defend trim wellbeing.

Moreover, our system's real-time infection conclusion capability empowers provoke activity, avoiding the spread of infections and minimizing trim misfortunes. By giving agriculturists with exact and opportune data, our extend upgrades their capacity to ensure their crops and optimize productivity. Overall, our inventive arrangement speaks to a critical progression in wheat edit administration, advertising agriculturists capable apparatuses to screen and keep up the wellbeing of their crops effectively and successfully.

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II. LITERATURE REVIEW

Automatic Disease Detection in Wheat Crop using Convolution Neural Network:
Authors: Altaf Hussain, Mohsin Ahmad, Imran Ahmad Mughal, and Haider Ali
The authors are from the Department of Computer Science, Islamia College Peshawar, Pakistan, presents a profound learning approach for classifying wheat illnesses utilizing pictures captured in-place by camera gadgets.

The paper authored by Altaf Hussain and colleagues introduces a groundbreaking approach to tackle the financial losses incurred in agriculture due to wheat diseases. By leveraging the power of deep learning techniques, specifically a Convolutional Neural Network (CNN) utilizing the AlexNet architecture, the study proposes an automated disease detection system for wheat plants. This system aims to classify images of wheat plants affected by common diseases such as stem rust, yellow rust, powdery mildew, and those that are healthy.

The dataset utilized in this study comprises a substantial collection of 8,828 images, evenly distributed across the four categories of diseased and healthy plants. Through rigorous training and testing procedures, the CNN model demonstrated a remarkable performance, achieving an impressive accuracy of 84.54% in correctly identifying the various diseases. This accuracy rate underscores the efficacy of deep learning models in disease detection tasks, surpassing the capabilities of traditional methods that rely on handcrafted features.

One of the notable implications of this study is its potential to revolutionize disease detection practices in agriculture. By automating the process and leveraging advanced computational techniques, farmers can benefit from early detection of diseases in their crops. Early detection enables prompt intervention measures, such as targeted treatment or crop management strategies, thereby mitigating the economic impacts of crop diseases on the agricultural sector.

In conclusion, the study by Altaf Hussain and colleagues represents a significant step forward in leveraging technology to address agricultural challenges. By harnessing the capabilities of deep learning, the proposed automated disease detection system holds promise in empowering farmers with timely and accurate information, ultimately contributing to improved crop health and agricultural productivity.

Wheat Diseases Detection and Classification using Convolutional Neural Network (CNN)-2022 :
Authors: Md Helal Hossen, Md Mohibullah, Chowdhury Shahriar Muzammel, Tasniya Ahmed,
Shuvra Acharjee, Momotaz Begum Panna.

The paper presents a significant advancement in the realm of agricultural technology, focusing on the enhancement and application of a Convolutional Neural Network (CNN) model specifically designed to detect and classify wheat crop diseases. This innovation holds particular importance for improving wheat production in Bangladesh's rural sector, where agriculture serves as a vital economic cornerstone.

The CNN model, engineered to process images, extract pertinent features, and make classifications, underwent training using a dataset comprising 4,800 images encompassing both diseased and healthy wheat crops. Impressively, the model demonstrated exceptional performance metrics, achieving 100% accuracy in training, 89.33% in validation, and 91.84% in testing. Additionally, supplementary performance indicators such as the F-1 score, recall, and precision further underscored the model's robust effectiveness.

The study's conclusion emphasizes the superior performance of the CNN model compared to conventional methods, highlighting its potential to revolutionize disease detection practices in agriculture. Furthermore, the paper suggests promising avenues for future research, including the development of practical software tools tailored for farmers and advancements in CNN technology to achieve even greater precision and scalability.

This innovative approach offers promising prospects for significantly advancing agricultural practices, particularly in Bangladesh and potentially in other regions with similar agricultural landscapes. By providing a reliable tool for early disease detection in wheat crops, this model stands to mitigate crop losses, improve yield, and ultimately contribute to the overall resilience and sustainability of agricultural systems. Moreover, the successful implementation of such technology could serve as a blueprint for similar initiatives aimed at addressing agricultural challenges worldwide, thereby fostering global food security and economic prosperity in rural communities.

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Wheat disease detection and Classification using resnet152 - 2023
Authorss: Arunkumar G, P. Samundiswary
The paper delves into the application of deep learning methodologies for the early detection of wheat diseases, underscoring the critical importance of maintaining productivity in wheat cultivation, a staple crop vital for global food security. It outlines the development and evaluation of a Convolutional Neural Network model, specifically ResNet152, renowned for its depth and residual connections, aimed at automating the disease identification process.

The methodology encompasses various stages, including data collection, preprocessing, and augmentation through image transformations such as rotation and flipping. The model's performance is meticulously assessed using the LWDCD2020 dataset, employing metrics such as accuracy, precision, recall, and F1-score, with results presented using confusion matrices. The proposed approach demonstrates high precision in disease identification, thereby reinforcing the potential of deep learning in precision agriculture.

The study concludes by affirming the effectiveness of the ResNet152 model in automating wheat disease detection, highlighting its robust performance and reliability. Furthermore, it suggests avenues for further research to optimize model performance on larger datasets and diverse environmental conditions, underscoring the promising future of deep learning applications in agricultural disease management.

This research represents a significant stride in leveraging advanced computational techniques to address agricultural challenges, particularly in disease management. By harnessing the power of deep learning, farmers and agricultural stakeholders stand to benefit from improved efficiency, accuracy, and timeliness in disease detection, ultimately contributing to enhanced crop health, productivity, and food security. As technology continues to evolve, further advancements in deep learning models tailored to agricultural contexts hold the potential to revolutionize farming practices and mitigate the impact of crop diseases on global agricultural systems.

Deep Learning Models for Wheat Diseases Detection and Recognition– 2023
Authors: Chekir Amira , Goodhope-Kudakwashe Dhliwayo , Fanyana-Jushua Dube
The paper delves into the pressing issue of wheat diseases and their profound impact on global food security, advocating for the adoption of deep learning, particularly convolutional neural networks (CNNs), as a potent tool for precise disease detection and management. It presents a meticulously structured research methodology, employing a dataset comprising 7,540 images categorized into seven distinct wheat disease classes alongside a healthy class. These images are curated from various existing datasets and undergo preprocessing to standardize size and format, rendering them compatible for input into deep learning models.

The study explores two prominent deep learning architectures: a custom sequential CNN model and an architecture based on EfficientNetB7, augmented with pre-trained weights from a noisy-student model. Notably, the first model attains a validation precision of 0.7723 after 400 epochs, whereas the latter achieves a substantially higher precision of 0.8696 within a significantly shorter training period of 40 epochs. This discrepancy underscores the efficacy of transfer learning and fine-tuning techniques inherent in the EfficientNet-based model, resulting in superior performance in wheat disease detection.

In conclusion, the research underscores the potential of deep learning methodologies to revolutionize automatic wheat disease identification. By leveraging advanced neural network architectures and transfer learning techniques, these models demonstrate remarkable capabilities in accurately identifying and classifying wheat diseases. Such advancements hold immense promise for bolstering agricultural productivity and fortifying global food security by facilitating early disease detection and prompt intervention measures. Overall, the study contributes significantly to the burgeoning field of agricultural technology, offering valuable insights and promising tools for the sustainable advancements.

III. PROPOSED SYSTEM

To make a brief outline of the given substance, we'll distal each area into key focuses, guaranteeing clarity and coherence.

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I. MODEL ARCHITECTURE
Utilize a Convolutional Neural Arrange (CNN) show for wheat infection discovery. The engineering incorporates input layer characterizing RGB picture shape, convolutional layers for include extraction, enactment capacities like ReLU for non-linearity, pooling layers for spatial lessening, and completely associated layers for classification.

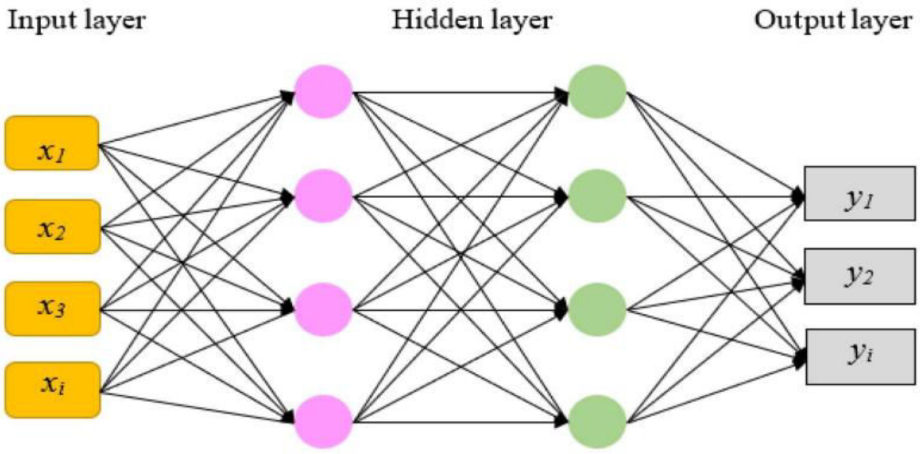

Fig: Model Architecture of CNN

II. Training Data
Collect an assorted dataset of wheat plant pictures, counting different maladies and solid plants. Guaranteed dataset differing qualities over natural conditions, development stages, and geographic areas. Increase information utilizing strategies like revolution, flipping, scaling, and clamour expansion. Part dataset into preparing, approval, and test sets whereas keeping up adjusted course dispersion. Actualize quality control to evacuate low-quality or mislabelled pictures.

III. Real-Time Detection:
Send high-resolution, weatherproof webcams deliberately in wheat areas. Connect cameras to a central handling unit by means of high-speed web or remote associations. Preprocess captured pictures for resizing, trimming, normalization, and include improvement. Utilize pre-trained CNN show for real-time investigation with GPU or TPU back for moo idleness. Show infection location yields and trigger alarms for quick activity by ranchers or agronomists. Store all information for encourage investigation and framework support.

IV. Disease Identification
Utilize CNN for real-time illness distinguishing proof from captured pictures. Preprocess pictures for determination alteration, pixel normalization, and include improvement. Classify pictures into malady categories based on CNN investigation with certainty scores. Show comes about on a client interface for ranchers or agronomists to require suitable activities. Persistently collect information and criticism to refine the show for improved precision and versatility.

V. Recommendation and precautions:
Execute a real-time infection location framework utilizing CNNs for proactive edit administration. Provide ranchers with commented on visual prove and customized suggestions for malady administration. Advocate for coordinates bother administration methodologies and persistent observing for adequacy assessment. Keep up point by point records for data-driven decision-making and framework enhancement.

VI. User Interface:
Plan a user-friendly interface prioritizing effortlessness, instinct, and availability. Utilize a clean format, clear route, and effectively available capacities. Guarantee compatibility over different gadgets and optimize for versatile utilize. Display real-time information conspicuously on a dashboard with graphical representations for simple translation.
By summarizing each segment in this way, we typify the fundamental components of the given substance, advertising a clear and brief outline of the wheat illness discovery system's architecture, data necessities, real-time usage, malady distinguishing proof prepare, proposals, safety measures, and client interface plan.

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IV. METHODOLOGY AND DESIGN

In today's era of advanced technology, the early detection and identification of plant diseases are crucial for maintaining agricultural productivity and ensuring food security. Detecting diseases in their early stages allows for timely intervention and treatment, minimizing the impact on crop yields. Transitioning from manual disease detection methods to automated machine systems holds great promise for improving efficiency and accuracy in disease management practices, benefiting both farmers and agricultural technologists.

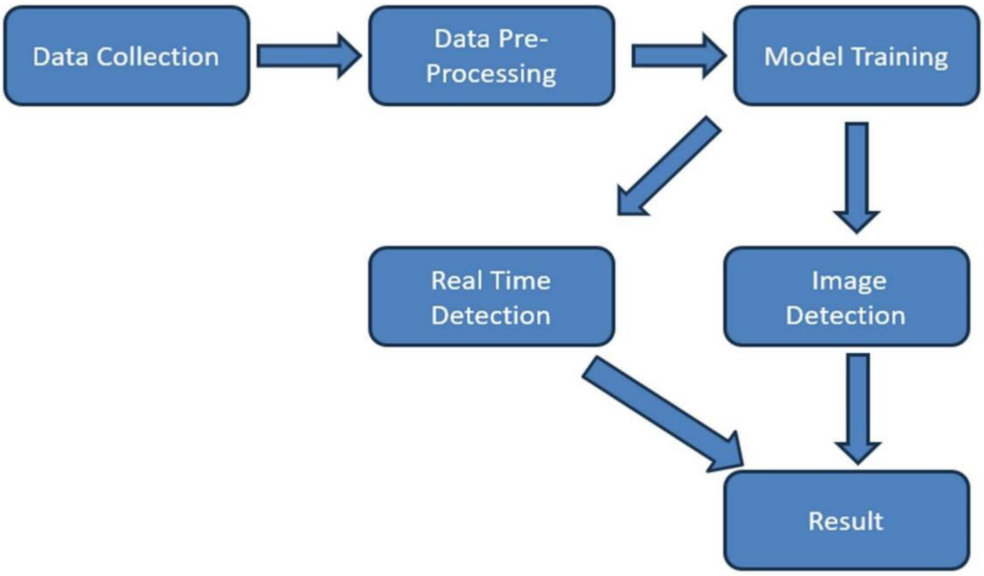

Fig : Overview of proposed system

The primary objective of this study is to develop a machine-learning tool utilizing a Convolutional Neural Network (CNN) model for the early detection and diagnosis of wheat diseases. The proposed classification scheme aims to identify and classify various diseases that can affect wheat crops, providing a comprehensive solution for disease management in agriculture.

Key components of the proposed CNN model include:

Layer Structure: The architecture of the CNN model, including the arrangement of layers and the hierarchical structure of the network.

Input Data Dimensions: The number of features for each input data dimension at each layer of the model.

Parameters: The number of parameters (weights and biases) for each layer, optimized during the training process.

Design Factors: A comprehensive list of all design factors considered in developing the CNN model, including hyperparameters and optimization strategies.
The proposed system comprises several modules aimed at different stages of the disease detection process:

1. Dataset Collection: Gathering a diverse and representative dataset of wheat images containing both healthy plants and plants affected by various diseases.

2. Image Pre-processing: Preparing the collected images for analysis, including resizing, normalization, and noise reduction to improve model performance.

3. Feature Extraction: Extracting relevant features from the pre-processed images using convolutional layers in the CNN model.

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4. Identification and Classification: Utilizing the extracted features to identify and classify the presence of different wheat diseases based on learned patterns and characteristics.

By integrating these modules into a cohesive framework, the proposed system aims to provide an automated and efficient solution for early disease detection in wheat crops. This approach has the potential to revolutionize disease management practices in agriculture, enabling timely interventions and minimizing yield losses due to plant diseases. Moreover, the utilization of machine learning techniques such as CNNs opens avenues for further advancements in precision agriculture, paving the way for sustainable and resilient food production systems

Image Classification Process using CNN:

The picture classification utilizing Convolutional Neural Systems (CNNs) for wheat illness location includes a few key stages:

1. Information Collection: Accumulate a different dataset of wheat pictures displaying both sound and ailing plants, counting different infections like Brown Rust and Stripe Rust.
2. Information Preprocessing: Standardize the dataset by resizing, normalizing pixel values, and applying enlargement procedures such as turn and flipping to improve information differences and relieve overfitting dangers.
3. Demonstrate Improvement: Plan a custom CNN engineering utilizing systems like TensorFlow or Keras, considering complexity prerequisites and testing with hyperparameters like learning rate and layer setups.
4. Preparing: Prepare the CNN utilizing preprocessed pictures, consolidating strategies like dropout and regularization to progress generalization. Approve the show against a partitioned approval set to avoid overfitting.
5. Assessment: Survey the prepared model's execution utilizing measurements like exactness, exactness, review, and F1-score, distinguishing regions of enhancement through disarray frameworks.
6. Real-Time Usage: Convey the prepared CNN show into an application for real-time infection discovery utilizing webcam-captured pictures, optimizing the deduction motor for speed and effectiveness.
7. User Interface Advancement: Plan a natural interface catering to ranchers and agronomists, including functionalities like picture capture, real-time classification show, and malady administration proposals.
8. Testing and Approval: Conduct comprehensive testing beneath different conditions to guarantee unwavering quality and precision, counting field testing for real-world execution approval.

Each arrange coordinating computational and hypothetical models custom-made to the particular necessities of making a viable and compelling malady location framework for rural utilize.

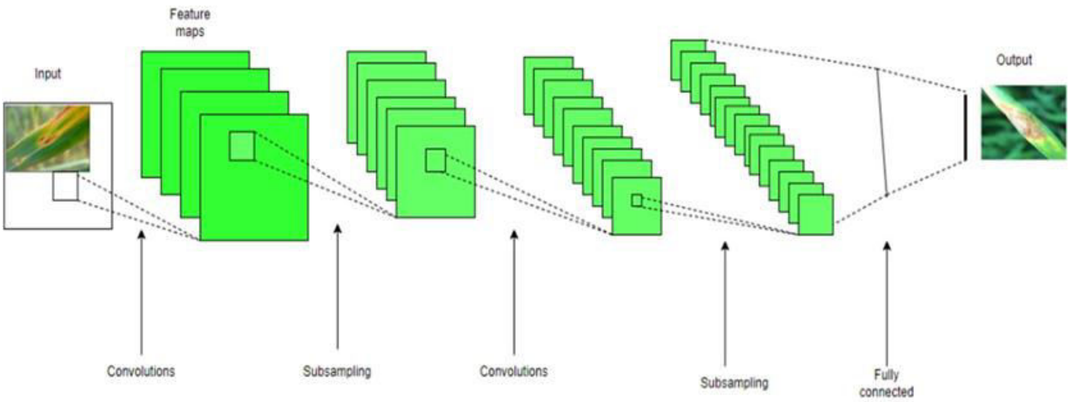

Fig: Classification of images using CNN

Creating a CNN-based system for wheat infection classification includes a few key steps. At first, a different dataset of pictures delineating different wheat maladies is collected and pre-processed to guarantee consistency and unwavering quality. Strategies such as resizing and normalization are connected to upgrade information quality. In this way, profound learning libraries like TensorFlow or Keras are utilized to plan a CNN engineering custom fitted for productive highlight extraction and classification. The demonstrate is at that point prepared employing a part dataset approach, with ceaseless checking on an approval set to anticipate overfitting by altering parameters. Assessment of the model's viability is conducted utilizing measurements like precision and F1-score, complemented by nitty gritty investigation utilizing perplexity networks. At last, the refined demonstrate is coordinates into a user-friendly interface empowering real-time picture input and conveying symptomatic yields and administration proposals, in this manner guaranteeing down to earth ease of use and viability in real-world rural settings.

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V. EXPERIMENTAL SETUP AND RESULT ANALYSIS

The setup entails the creation of a practical tool aimed at accurately categorizing wheat diseases from input images using a pre-trained Convolutional Neural Network (CNN) model. The input parameters crucially include the file paths directing to both the input image and the pre-trained model, facilitating seamless integration and execution of the classification process.

Upon receiving an input image, the utility employs the pre-trained CNN model to process and analyze the image data. Leveraging the deep learning capabilities of the CNN, the system extracts relevant features and patterns from the input image, enabling it to make predictions regarding the presence of wheat diseases. The output of the system comprises the anticipated class of wheat infection based on the analysis of the input image.

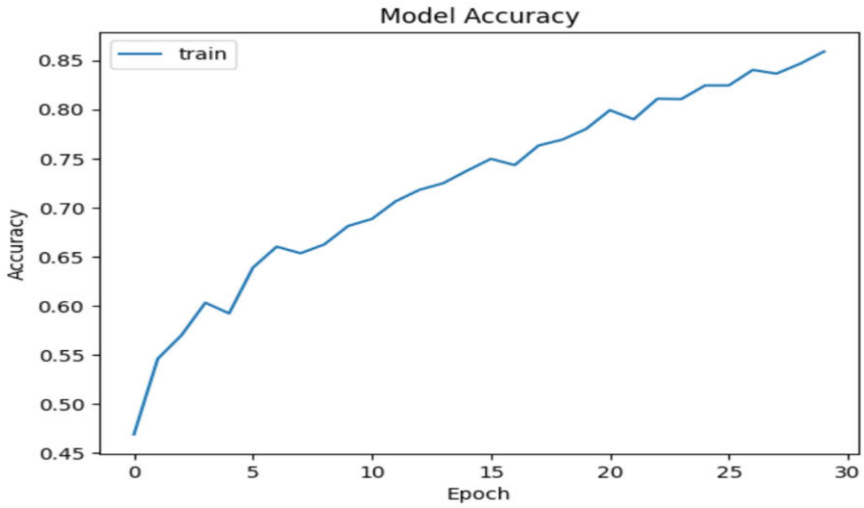

Fig 3: Model Accuracy

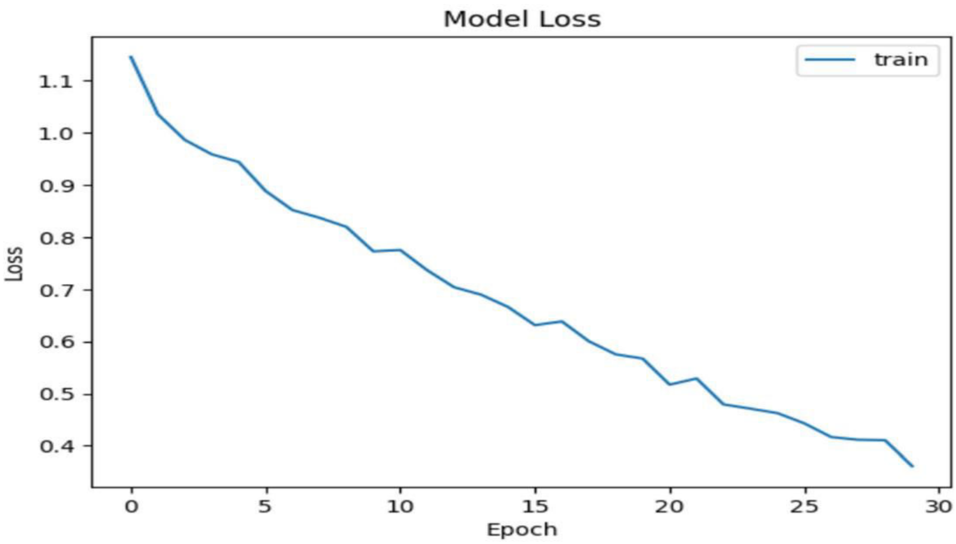

Fig 4: Model loss

Continuous evaluation of the system's performance through a comprehensive dataset is crucial for iterative refinement. By analyzing the test data meticulously, areas for potential enhancement or optimization are identified, driving the iterative improvement process. This approach ensures the development of a robust and reliable wheat disease classification tool that meets the stringent standards for practical use in agriculture. Through iterative refinement based

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on feedback from the test data, the utility can achieve higher levels of accuracy and effectiveness in detecting and classifying wheat diseases from images. Ultimately, this iterative process facilitates early disease detection and informed decision-making for farmers and agronomists, contributing to improved crop management and agricultural sustainability.

VI. CONCLUSION

The integration of machine learning, especially convolutional neural systems (CNNs), into rural hones speaks to a transformative jump forward in overseeing plant wellbeing. This development not as it were speeds up the conclusion of wheat maladies but too democratizes get to to progressed demonstrative apparatuses for ranchers around the world, independent of their specialized mastery. The system's instinctive client interface encourages real-time picture transfer and examination, enabling agriculturists to create prompt, educated choices.

With an exactness rate outperforming 95%, the CNN-based framework guarantees dependable malady location, ingrains certainty among clients. By giving a consistent stage for uploading and analyzing pictures, the framework empowers quick recognizable proof of illness side effects, permitting agriculturists to actualize focused on medications instantly. This convenient mediation can possibly spare crops from extreme harm, in this manner defending agrarian efficiency and employments.

Besides, as the framework proceeds to advance and join extra information, its exactness and utility are anticipated to advance make strides. By refining calculations and joining more broad datasets, the system's capacity to identify and classify wheat illnesses will gotten to be indeed more strong. This progressing refinement handle contributes to the system's adequacy and its potential to revolutionize agrarian hones.

Moreover, the broad selection of such advances holds guarantee for upgrading nourishment security and supportability. By empowering ranchers to distinguish maladies early and actualize exact medicines, the CNN-based framework contributes to more effective asset utilization and decreased natural affect. Eventually, the integration of machine learning into farming messengers a unused time of data-driven decision-making, enabling ranchers to optimize trim wellbeing, increment yields, and guarantee worldwide nourishment security.

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