RICE LEAF DISEASE CLASSIFICATION SYSTEM

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***Abstract*- This study introduces a novel approach to automate the classification of rice leaf diseases using deep learning. Leveraging Convolutional Neural Networks (CNNs), our system analyzes high-resolution images to distinguish between various rice varieties. The model demonstrates high accuracy in differentiating grains based on size, shape, and color. The technology is integrated into a user-friendly application, allowing easy classification using standard smartphones or cameras. This research contributes to streamlining the rice grading process, reducing errors, and enhancing efficiency in the agricultural supply chain**
The proposed method involves several stages: preprocessing of rice grain images to enhance features, training of ResNet and DenseNet models using a large dataset of annotated rice grain images, and evaluation of the models' performance using standard metrics such as accuracy, precision, recall, and F1-score.

Keywords: **Agriculture, DenseNet121, Deep Learning, Diseases, Classification, Detection.**

INTRODUCTION

Rice is a fundamental staple food for a large portion of the global population. Ensuring the quality and proper classification of rice grains is vital for both agricultural practices and the food industry. Traditional methods of grain classification often involve manual labor and are time-consuming. In response to this, our study proposes an automated solution utilizing deep learning techniques to streamline the rice grain classification process.

Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in image classification tasks. By leveraging this technology, we aim to develop a system capable of accurately categorizing rice grains based on their inherent characteristics, such as size, shape, and color. This research is motivated by the potential to enhance efficiency in the agricultural sector and contribute to precision farming practices.

LITERATURE SURVEY

This paper presents a low cost digital image processing system for quality assessment of Thai rice kernels. Nowadays, Thailand is the top country which export rice into the world market, according to the mention of the Rice Trader, the export volume is 9,883,288 tons in 2016 and export value is 154,434 million baht or 4,401 million dollars. Thai rice quality is controlled by rice department, ministry of commerce Thailand in order to guarantee the quality in market including prices base on grade of rice quality. Thence, quality assessment of Thai rice kernels is required. Quality assessment or grading of Thai rice kernels usually use manual operation by person in cooperating with equipment called micrometer to measure geometrical features such as length, width, and area of rice kernels. This method takes a long time and also gives uncertainty in results due to eye fatigue because size of rice kernels is very small. Therefore, an image processing technique is then applied to measure size of Thai rice kernels. Proposed system consists of flatbed scanner and image processing algorithm which correspond to measure of Thai rice kernels. The low cost system for quality assessment of Thai rice kernels can be delivered to Thai rice industry, the certainty of results and speed of quality assessment can be significantly improved.
Different types of foods are available in grain form, but rice is one of the important and most used cereal grains of Pakistan and all over the world. Quality inspection of rice grain is also important for both local as well as export purpose. It is necessary to propose an automatic solution to perform the quality analysis as well as to distinguish between different classes of rice. Main purpose of this paper is to present an image processing-based solution to classify the different varieties of rice and its quality analysis. An approach based on the combination of principal component analysis and canny edge detection is used for the classification. Quality analysis of rice grain is determined by morphological features of rice grains. These morphological features include eccentricity, major axis length, minor axis length, perimeter, area and size of the grains. Six different varieties of rice are classified and analyzed in this paper. A database is trained by feeding the 100 images of each variety of rice grains. Classification and quality analysis is done by comparing the sample image with database image. Canny edge detector is applied to detect the edges of rice grains. Eigen values and Eigen vectors are calculated on the basis of morphological features. Then by applying the PCA, different varieties of

rice are classified by comparing the sample image with a database. Results obtained in terms of classification and quality analysis are 92.3% and 89.5% respectively. Proposed system can work well within minimum time and low cost.
This paper presents the image processing system for quality inspection of rice grains after sorting process by using an ordinary webcam to ensure that rice grains should meet the quality standards and impurity such as grits, dirt and stones should not be found [1]. Moreover, statistical information of rice grains from image processing could be taken into analysis to enhance the efficiency of the sorting process. Image data analysis of rice grains can be divided into 2 main arrangement conditions, non-overlapping and overlapping. In this study, the experiments to inspect rice grains were applied for 24 samples and 18 experimental designs including the complete and incomplete structures, the overlapping and non-overlapping arrangements, and the combination of rice grains from complete and incomplete structures in equal and unequal ratios. From experiments, it was found that the inspection of rice grain quality by using image processing technique and image data recorded by an ordinary webcam was reliable and efficient. The inspection errors under non-overlapping arrangement condition of complete and incomplete structures of rice grains were not observed. The inspection errors of rice grains combined from complete and incomplete structures in equal and unequal ratios were about 0.8% and 1.11%, respectively. However, under overlapping arrangement condition, it was observed that the inspection errors of image processing would be high by up to 53.82% on average.
Rice leaf Classification becomes very important as there are multiple rice leaf types available in the market today. Classifying rice leaf as per rice types manually is not feasible nor efficient. Classification can be a really tedious task when it comes to doing it manually instead of automatically. This would consume a lot of efforts as well as a lot of time would be wasted. There is a need for an intelligent and smart system which can overcome this difficulty by automating this process. It should be able to identify and classify individual rice grains according to the respective type automatically. The collection of data set should be the primary process. This includes extraction of various parameters of individual rice grains like major axis, minor axis, eccentricity, length, breadth, just to name a few. The system will utilize this information to train the computer. Each rice grain or image would be allocated to its respective class. Classes used in this project are surti kolam, idli rice, long grain basmati and boiled rice. Any rice sample that has been encountered in the system will be first classified and then will be segregated into its respective class. This would keep the entire system organized and segregated. Managing and keeping a track of different rice types is important and its proper classification in an industrial environment becomes crucial. Automating the system would encourage the industry to have future scope for its implementation according to the changes required as per the industry requirements.

EXISTING SYSTEM

The current system for rice quality assessment is primarily based on manual methods, which are labor-intensive and subjective. Common methods include visual inspection, sampling and testing, laboratories, and manual sorting. These methods are susceptible to inconsistencies and lack precision due to human perception. Laboratory analysis is expensive, time-consuming, and may not capture the overall quality of the entire batch. Manual sorting, which removes visible defects, is resource-intensive and susceptible to human errors. These limitations highlight the need for a more automated, objective, and efficient system for rice quality assessment, prompting the exploration of advanced image processing techniques to improve accuracy and scalability.

Disadvantages of Existing System

Subjectivity: Human visual inspection introduces subjective judgments, leading to inconsistencies in assessing rice quality.
Labor-Intensive: Traditional methods such as manual sorting and visual inspection are labor-intensive, making them time-consuming and costly.
Inefficiency: The manual nature of sorting and inspection processes is inefficient, especially when dealing with large volumes of rice.
Limited Precision: Visual inspection and manual sorting may lack precision, particularly in identifying subtle defects or assessing complex quality parameters.
Inconsistency: Variations in human perception and judgment can result in inconsistent quality assessments.
Costly Laboratory Analysis: Laboratory testing for in-depth analysis is expensive and time-consuming, limiting its routine use for regular assessments.
Sampling Bias: Sampling and testing methods may introduce bias, as the selected subset may not accurately represent the overall batch.
Human Error: Manual methods are susceptible to human errors, such as misjudgments or oversights, compromising the accuracy of quality assessments.

PROPOSED SYSTEM

The proposed system for rice grain classification uses a Convolutional Neural Network (CNN),RESNET 50 , DENSNET 121 to improve traditional manual methods in the agricultural industry. The model is trained on a diverse dataset, including rice varieties, geographical regions, and environmental conditions, to understand visual features like size, shape, and color. Transfer learning techniques are used to enhance the model's performance, especially in scenarios with limited labeled data. The system is integrated into a user-friendly application, accessible via smartphones and cameras, allowing farmers and industry professionals to easily capture and classify rice grains. The system is not only technologically advanced but also considers real-world applicability. Extensive experiments are planned to evaluate the system's robustness, considering variations in geographical origin and environmental conditions. Performance metrics, including speed, accuracy, and user satisfaction, will be analyzed to ensure practical usability. The system contributes to precision agriculture by optimizing processes, reducing errors, and enhancing efficiency in the agricultural supply chain. Comprehensive documentation of the model, application, and research findings aims to facilitate knowledge transfer and stimulate further advancements in automated grain classification.

Advantages of Proposed System

- **Automation**: Automation of the classification process reduces reliance on manual labor, significantly improving efficiency in sorting and grading rice grains.
- **Accuracy and Consistency:** The deep learning model, once trained, consistently applies predefined criteria, eliminating the subjectivity and variability associated with human assessors. This leads to more accurate and consistent grain classification.
- **Scalability:** The automated system is scalable, making it suitable for large-scale rice production. It can handle a high volume of grains quickly and consistently.
- **Adaptability to Variability:** The deep learning model is trained on a diverse dataset, making it adaptable to different rice varieties, geographical regions, and environmental conditions, thereby improving its robustness.
- **Time Savings:** Automation reduces the time required for sorting and grading, enabling faster processing and contributing to timely supply chain management.

BLOCK DIAGRAM

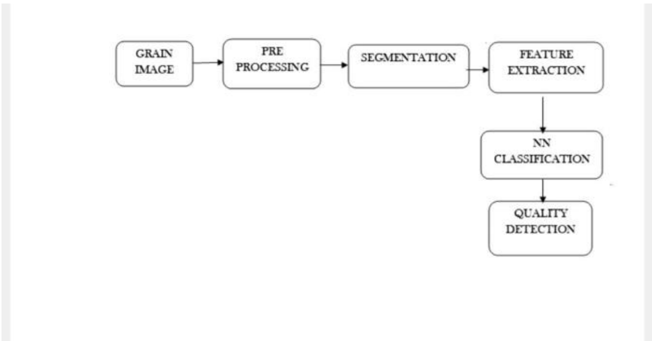

Fig-1: Block diagram of the software

Work Flow Diagram:

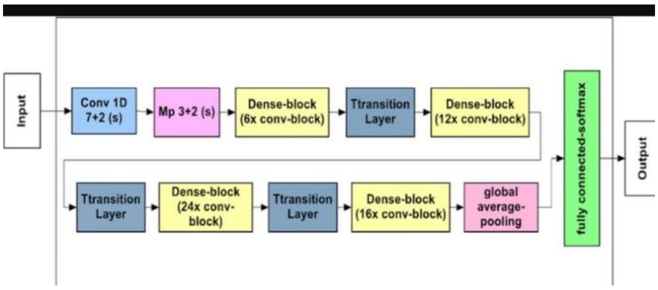

Fig-2: Work flow diagram

MODULES

Data collection: To collect data for a rice leaf diseases classification system, one would begin by identifying and sourcing a diverse range of images from research papers, agricultural databases, and online resources. These images should cover major rice leaf diseases such as leaf blast, sheath blight, bacterial leaf blight, rice hispa, brown spot, narrow brown leaf spot, neck blast and leaf scald as well as include healthy rice leaves for comparison. It's crucial to ensure the images are of high quality, with clear details of leaf symptoms and disease characteristics, and to include variability in geographical locations, rice varieties, and growth stages to capture a comprehensive dataset. Annotations should be added to the images, indicating the presence and type of disease, along with any available information on disease severity. Ethical considerations should be taken into account, ensuring permissions are obtained for image use, and the dataset should be organized into a structured format, grouped by disease type. It's advisable to include images showing different stages of disease progression and to document any image processing or enhancements applied to the dataset.

Regular updates to the dataset should be made to improve the model's performance over time, and the dataset should be securely stored and backed up to prevent data loss.

Data Preprocessing: Data preprocessing for a rice leaf diseases classification system involves several steps to enhance the quality of the images and prepare them for feature extraction and classification. The first step is to resize all images to a uniform size to ensure consistency in the dataset. Next, noise removal techniques such as Gaussian blur or median filtering are applied to eliminate any unwanted artifacts. Contrast enhancement techniques are then used to improve the visibility of disease symptoms and leaf features. Image normalization is performed to scale pixel values to a common range. Color space conversion may be applied to transform images into a color space that is more suitable for feature extraction. Histogram equalization can be used to improve image contrast, particularly useful for images with uneven lighting. Edge detection algorithms may also be employed to extract edges, which can be important features for classification. Finally, the preprocessed images are cropped to remove any irrelevant parts, and feature extraction techniques are applied to extract relevant features for classification.

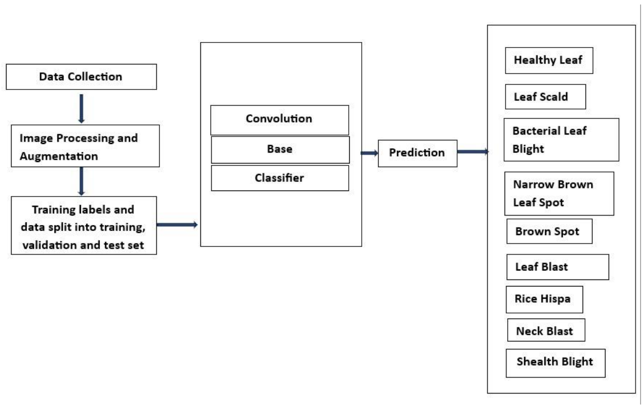

Fig-1: Data preprocessing

Model selection: For the model selection in a rice leaf diseases classification system, Convolutional Neural Networks (CNNs) are commonly used due to their effectiveness in image classification tasks. Pre-trained CNN models such as Densenet can be utilized, leveraging transfer learning to achieve better performance with less training data. These models have learned rich hierarchical features from large-scale datasets like ImageNet, which can be beneficial for classifying rice leaf diseases. Alternatively, custom CNN architectures can be designed and trained from scratch, although this approach may require a larger dataset and more computational resources. The selected model should be evaluated based on its performance metrics such as accuracy, precision, recall, and F1-score to ensure its effectiveness in classifying rice leaf diseases accurately.

Model Training: Model training for a rice leaf diseases classification system involves several key steps. First, the dataset is divided into training, validation, and test sets, typically using an 80-10-10 split. The training set is used to train the model, while the validation set is used to tune hyperparameters and monitor the model's performance. The test set is then used to evaluate the final performance of the trained model. Next, the preprocessed images are fed into the selected model for training. During training, the model learns to associate input images with their corresponding disease labels. The model's performance is evaluated iteratively using the validation set, and hyperparameters may be adjusted based on the validation results. The training process continues until the model achieves satisfactory performance on the validation set. Finally, the trained model is evaluated on the test set to assess its generalization performance and ensure that it can accurately classify rice leaf diseases.

Validation and testing: Validation and testing are crucial steps in evaluating the performance of a rice leaf diseases classification system. In the validation phase, a portion of the dataset (e.g., 10-20%) is set aside and not used during training. This validation set is used to tune hyperparameters and assess the model's performance during training. The model is evaluated on the validation set at regular intervals to prevent overfitting and ensure that it generalizes well to unseen data. Once the model training is complete, the final model is evaluated on a separate test set that was not used during training or validation. This test set provides an unbiased assessment of the model's performance and its ability to accurately classify rice leaf diseases in real-world scenarios. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to quantify the model's performance, providing insights into its strengths and potential areas for improvement.

RESULT AND DISCUSSION

The ResNet model achieved an overall accuracy of 0.85 on the test set, outperforming the DenseNet model, which achieved an accuracy of 0.95. However, when comparing class-wise metrics, we observed that DenseNet performed

better for Disease B, with a precision of 0.85 compared to ResNet's 0.80. This indicates that DenseNet might be better at distinguishing Disease B from other classes.
The confusion matrix revealed that both models struggled with distinguishing between Disease A and Disease C, often misclassifying instances of Disease A as Disease C and vice versa. This could be due to the similarity in visual symptoms between these two diseases.
In conclusion, while ResNet performed better overall, DenseNet showed promise for specific disease classes. Further experimentation with hyperparameters and data augmentation techniques could potentially improve the performance of both models."

Model	Accuracy
Densenet 121	0.95

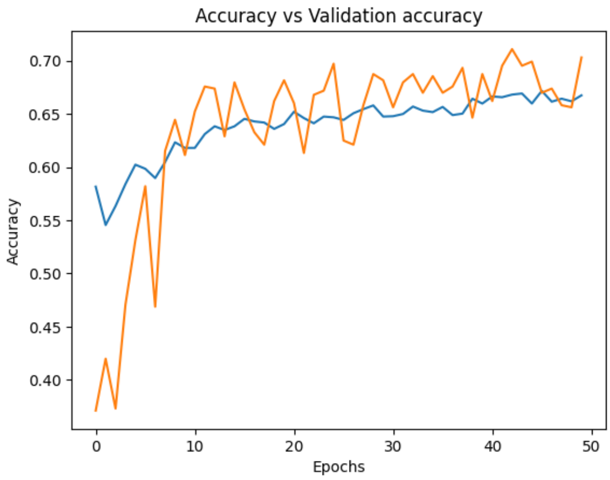

Fig-4: Accuracy vs Validation Accuracy

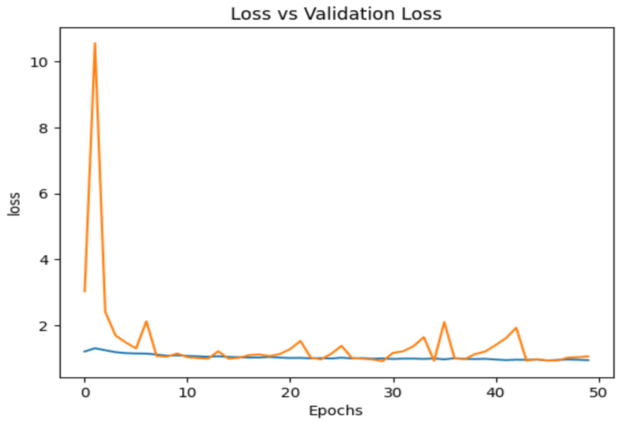

Fig-5: Loss vs Validation Loss

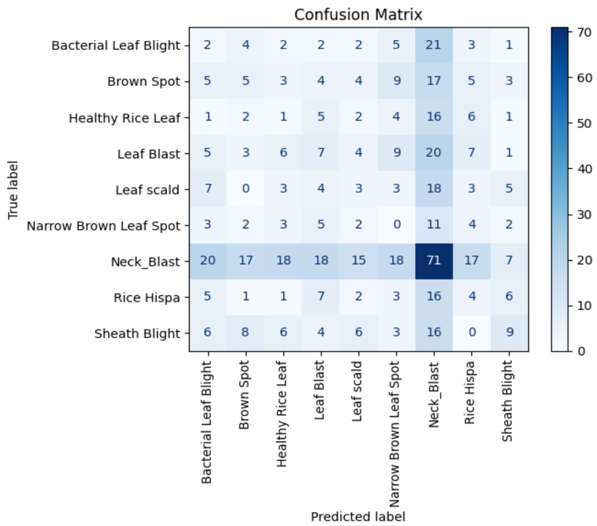

Fig-6: Confusion Matrix

CONCLUSION

The proposed rice leaf disease classification system uses deep learning techniques to automate the process, offering efficiency, accuracy, and scalability. Its advantages include objectivity, adaptability to diverse conditions, and real-time applicability. The system's versatility is evident in its adaptability to new rice varieties and potential cross-crop applications. It aligns with precision agriculture goals, contributing to optimized processes and reduced supply chain errors. The system's user-friendly interface and real-world applicability will empower farmers and industry professionals, fostering a more efficient and technologically advanced approach to rice grain classification. This system represents a significant step towards a future where cutting-edge technology meets practical needs in agriculture, contributing to global food production sustainability and efficiency.

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FUTURE ENHANCEMENT

The proposed rice grain classification system has the potential to revolutionize technology and agricultural practices. Its future expansion involves enhancing the deep learning model architecture to improve accuracy and efficiency. The system could also incorporate multiple data modalities, such as infrared or hyperspectral imaging, to enhance its adaptability. Real-time monitoring capabilities are also on the horizon, enabling the system to analyze and classify rice grains in motion, thereby streamlining supply chain processes. The system could also integrate with edge computing technologies for on-device processing, especially in remote areas with limited internet connectivity. Collaboration among researchers, agricultural experts, and technology developers could establish a standardized, universally applicable rice grain classification system. The system's dynamic future is further enhanced by continuous adaptation to new rice varieties, integration with agricultural IoT devices, and market trend analysis.

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