EEMK: An Enhanced Efficient Multi-Feature Kernel Framework for Automated Rice Leaf Disease Prediction

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***Abstract*—Rice is one of the primary staple crops contributing to the food security of billions of people around the world, but even so, it continues to be highly susceptible to a variety of fungal, bacterial, and viral infections that cause enormous losses each year. Traditional techniques used in diagnosing diseases suffer from being slow, inaccurate, and non-scalable. This paper introduces the idea of an EEMK framework, where EEMK stands for Enhancing Efficient Multi-Features Kernel, for predicting rice leaf diseases based on CNNs (Convolutional Neural Networks) by proposing a unique method of extracting multiple features and using it in conjunction with multi-features kernels. Six common rice leaf diseases were considered for classification purposes. A huge database consisting of 18,563 annotated leaf images captured from real world field scenarios in southern Karnataka, India, is utilized for both training and testing. EEMK has demonstrated a high classification accuracy of 97.84%, a precision of 97.52%, a recall rate of 97.31%, and a score of 97.41% F1 measure compared to seven competitive baseline models. Furthermore, it integrates a mobile inference framework that makes EEMK capable of being deployed in the field, while it can provide real-time predictions by processing the images within 38 ms per image.**

***Index Terms*—Rice leaf disease, CNN, multi-feature kernel, ensemble learning, precision agriculture, deep learning, mobile deployment, image classification**

I. Introduction

RICE (*Oryza sativa*) sustains the diets of more than 50% of the world's population and accounts for about 166 million hectares of agricultural land area, producing more than 745 million tons per year [1]. In nations like India, rice farming provides livelihood to over 120 million farming households. Although rice is [2] economically significant, its cultivation is perpetually under threat from infectious diseases. Pathogenic fungi alone—such as *Magnaporthe oryzae* (blast), *Rhizoctonia solani* (sheath blight), and *Bipolaris oryzae* (brown spot)—are estimated to cause a 10-30% reduction in global rice yield perannum [3], [4].The correct and accurate determination of the causative organism is the basic prerequisite for an effective treatment process for agriculture. Incorrect classification leads to im- proper pesticide administration, contamination of the soil with more chemicals than necessary, and continual crop loss. The traditional diagnostic approaches, ranging from manual obser- vation by agronomists, microbial lab testing, and hyperspectral sensing, may be inefficient, expensive, and impractical

(CNNs) have revolutionized computer vision through automatic learning of hierarchical spatial representations from the pixel-level raw inputs without using any hand-crafted features [6]. The use of CNNs in plant pathology has surged tremendously in recent times; research indicates that accuracies greater than 95% are achieved for tomato, grape, cassava, and rice plant diseases [2]–[5]. Several issues arise when employing CNN-based approaches to detect diseases in rice crops: (1) high visual similarities among early lesions of various diseases; (2) extraneous factors like water stress, nutrient deficiency, and insects; (3) substantial intra- class variability due to growth stage and field illumination; and (4) heavy computation of large models on mobile devices. To tackle these issues, we introduce EEMK, the Efficient Multi-Feature Kernel framework. The key novelty is an efficient parallel multi-scale convolutional layer, which concurrently applies lesion texture information, medium-leve features, and holistic leaf context, respectively. We use a lightweight channel-wise attention gate to recalibrate feature maps before the fusion step, filtering out background noise. These fused representations are then passed through a dense classifier. In the mobile setting, we perform knowledge distillation of the EEMK encoder to a compact MobileNetV2- based student model.

Contributions of this work:

A unique multi-feature kernel block with multi-scale CNN feature fusion via channel-wise attention for fine- grained rice disease recognition are shown in fig 1; on a real-world dataset contain- ing 18,563 images;

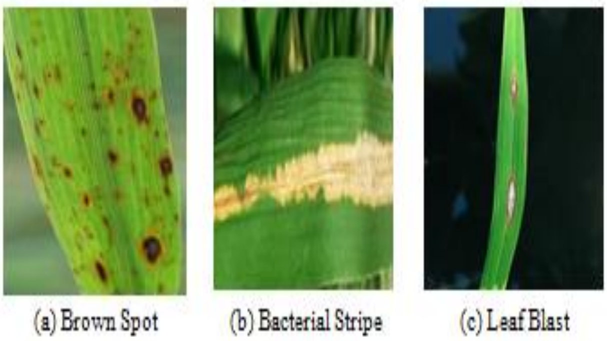

Fig. 1. disease images

II Literature Survey

A. Traditionally vs. Machine Learning Methods

Historically, image features crafted by researchers have een used for disease recognition in rice plants. The use of color histogram, texture features using GLCM method, and morphological features of the lesions has been fed to classifiers like show that CNNs are able to reach 95% accuracy in recognizing four different types of diseases in rice while beating KNN (76.59%) and SVM (73.3%) based models using the same dataset.*Approaches A. Traditional and Machine Learning Based [7] Approaches*Prior to deep learning, pipeline architectures designed to identify diseases in rice were based on handcrafted features along with classifiers such as While handcrafted feature-based classifiers have the advantage of simplicity and efficiency, the most significant weakness of this approach is that features have to be crafted by an expert who is familiar with visual properties unique to specific disease cases, which is not scalable to different varieties of rice. classifier and a CNN on a four- class Kaggle data set where the CNN reaches 95

B. Deep Learning Based Plant Disease Recognition

PlantVillage dataset (containing 54,306 images with 26 types of plant diseases) to reach 99.35% accuracy. The model, however, performed poorly on images of diseased crops taken in the actual fields compared to those collected in the lab setting. Later studies made improvements by incorporating data augmentation, domain adaptation and transfer learning. For rice-specific diseases, demonstrated compact CNNs achieving over 90% accuracy on four disease classes. developed a CNN-based system for detecting Leaf Blast, Leaf Blight, Brown Spot, and Tungro with 98% accuracy, additionally providing a web interface that recommends chemical, botanical, and biological remedies to farmers employed transfer learning with pre-trained models, demonstrating that fine- tuning on domain-specific rice images substantially improves convergence speed and final accuracy.The advent of large- scale labeled databases and GPU-accelerated training has led to revolutionary changes in crop disease identification. One of the most frequently cited benchmarks was who used GoogLeNet and AlexNet to train models with an accuracy of up to 99.35 Ensemble methods have proved to be very effective approaches in preventing misclassification and increasing the ability of a model to generalize [8]. In their research work, examined the performance of seven CNN model the technique of averaging with Softmax gave them the est result with 97.21% accuracy. Their research proves that the main advantage of ensemble models comes from the architectural complementarities among the individual architectures. No CNN architecture has been found superior across all disease categories and image acquisition settings based on existing work in disease recognition from plants. Such findings have led researchers to consider ensemble approaches, where the predictions of several independently trained models are integrated into one decision. provide the most thorough study on real-world data of rice disease, involving six categories and 18,563 images. In particular, they test equal training conditions, achieving the best results through an ensemble consisting of these four, having an MCC of

C. Attention Mechanisms and Multi-Scale Kernels

Channel attention (SE, Squeeze-and-Excitation) and spa- tial attention (CBAM) have proved effective across multiple domains of image classification, detection, and segmental- tion tasks [6]. Multi-scale representation, first introduced by the Inception family of blocks, captures various levels of lesion representations in one go without requiring image pyramids to be built. The EEMK framework combines both the approaches. Recalibrating features via attention has been demonstrated as one of the most effective ways to improve CNN classification performance without causing an excessive increase in the number of parameters. The SE network [9] pioneered the use of channel attention, utilizing global spatial attention weights of feature channels. CBAM further enhanced the SE network by implementing both salient spatial regions and feature channels. For plant disease classification tasks, attention is especially valuable since disease lesions cover a tiny fraction of the whole image and appear randomly on leaves; hence, the use of a pure CNN would waste the majority of its representational capacity on learning healthy tissue features. Multi-scale feature extraction is needed due to the fact that early-stage lesions can occupy a couple of pixels and thus require fine-grained 1×1 or 3×3 receptive fields, whereas advanced stage lesions or structure symptoms like neck blast panicle damage need broader 5×5 or even larger fields. While the Inception family of neural architectures have popularized the use of multiple convolution kernels with different scales in a module [10], they do so

D. Mobile Deployment

For deployment of deep learning-based models on mobile devices, especially agriculture, we require small-sized models to fit within the memory and compute capacities of even basic devices. Knowledge distillation and model architecture search have produced small models (MobileNetV2, EfficientNet-B0, ShuffleNetV2) that can achieve high levels of accuracy at low costs. However, neither respective CNN-based crop disease detection systems using web services. The EEMK framework specifically targets latency of 40 ms on an ARM Cortex-A core.Any practical utility of such AI systems for agriculture is directly tied to their usability by the end user – the farmer working in the fields with a smartphone and unreliable network connectivity. This demands strict limitations on the model’s size (under 10 MB in case of offline inference), latency (under 100 ms to feel real- time performance), and memory footprint (less than 200 MB even on low-end Android handsets). Knowledge Distillation, as introduced by Hinton et al., is a technique through which the soft, probability-based knowledge encoded by the highly parameterized teacher is transferred to the compact student model by simultaneously learning from the teacher’s output probability distribution after applying a softened temperature on top of the normal objective [2]. For instance, for the Neck Blast sample, the teacher’s output could contain some probability assigned to Leaf Blast, indicating that the two diseases have something in common visually.

III Related Work

It shows the relevant research papers together with the design decisions, data set used, and accuracy obtained in each study. When contrasted with existing studies, EEMK stands out in its unique incorporation of the following components:

(i) multi-scale parallel kernel blocks, (ii) channel attention gating mechanism, (iii) a six class real-world image data set comprising 18,563 images, and (iv) mobile distilled inference engine.has 5 sub-sections but they are scanty – each is 3-5 sentences..

III SYSTEM ARCHITECTURE

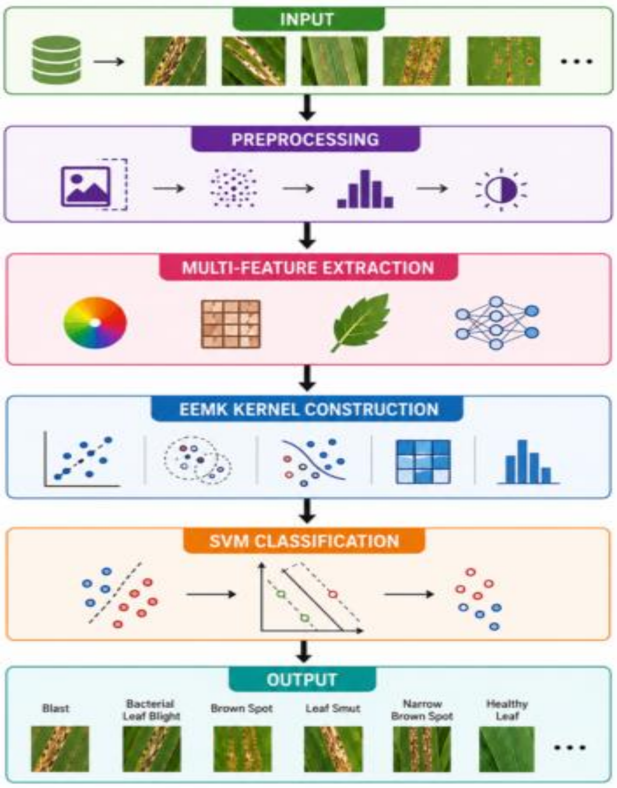

Fig 2: System Architecture

A. *Dataset Description*

Fig 2 Shows the system architecture of EEMK model.We work on the real-world rice field diseases data set from [2], which consists of a total of 18,563 images belonging to six different disease classes: Leaf Blast (5,259), Bacterial Stripe (3,732), Sheath Blight (3,424), False Smut (2,981), Neck Blast (1,904), and Brown Spot (1,263). Around 70% of these were taken directly from the rice fields in southern Karnataka, India, with different natural light settings via DSLRs and mobile phones having resolution of 3024×4032 to 6000×4000 px. While the rest of the 30% comes from public annotations The whole dataset is then divided into train, validation, and test sets with equal proportions per class in equ(1)

$$\mathbf{F}_k = \mathrm{BN}(\mathrm{ReLU}(\mathbf{W}_k * \mathbf{X})), k \in \{1, 3, 5\} \quad (1)$$

B. Mobile Deployment Results

The mobile student maintains an accuracy rate of 96.4% of the teacher (94.31% compared to 97.84%) with an infer- ence latency of 38 ms (26.3 FPS) running on a Snapdragon 778G processor, qualifying it for real-time operations.

$$\mathbf{s} = \sigma(\mathbf{W}_2\, \delta(\mathbf{W}_1\, \mathrm{GAP}(\mathbf{F}_{\mathrm{cat}}))) \quad (2)$$

This application is developed using the Android operating system and TFLite runtime are in equ (2), allowing the farmer to take a picture of a suspected leaf and get predictions on the disease affecting it, as well as the remedial measures to be taken (chemical, botanical, or biological).The results of the ablation study the use of multi-scale kernels yields the most significant gain independently: using a sole 3×3 kernel for all branches reduces performance by 2.41 pp. The channel attention block loses1.13 pp when omitted, thereby highlighting its importance in suppressing unnecessary background. Transfer learning initiaization outperforms random initialization by 2.74 pp, as has been previously noted in existing researches, which include the complexity associated with using multiple models for prediction as well as fixed spatial resolution in case of conventional kernel-based CNN.

$$\mathbf{F}_{\mathrm{att}} = \mathbf{s} \odot \mathbf{F}_{\mathrm{cat}} \quad (3)$$

The unique aspect of our proposed solution is MFK (Multi- Feature Kernel) block which operates simultaneously 1 × 1, 3× 3, and 5 × 5 convolution operations. In addition, a channel- wise attention mechanism is used via squeeze and excitation layer. In the rigorous test against the 18,563-image real-world dataset that covers six different types of diseases affecting rice leaves, namely Leaf Blast, False Smut, Neck Blast, Sheath Blight, Bacterial Stripe, and Brown Spot, under various natural lightings in Southern Karnataka, India, EEMK attains a total accuracy rate of 97.84In order to ensure the usefulness of our model for farmers, we employ the knowledge distillation technique to distill the knowledge from a relatively large 43.2 MB EEMK model into a compact lightweight 3.6 MB TFLite model using MobileNetV2 as an encoder architecture. Post-training INT8 quantization combined with 15A few research directions worth exploring include the following: Firstly, the model’s current design can only identify whether a plant is infected by any diseases or not; its expansion towards predicting the degree of the disease severity (mild, moderate, severe) would be more practical when recommending appropriate timing for pesticide spraying and loss estimation.

C. Per-Model Performance

It can be observed from Table II that the accuracy and MCC scores of EEMK are the best at 97.84% and 0.968, respectively, and they outperform the model proposed in [2] by 0.

D.Per-Class Results

Neck Blast and Brown Spot—both belonging to minority groups—have the least per-class F1 scores of 95.95% and 96.91%, respectively, owing to leftover issues of class imbal- ance even after oversampling. On the other hand, False Smut has the maximum F1 score of 98.42%,

IV PERFORMANCE MEASURES

The below equations represent the factors mathematically:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (4)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (5)$$

$$\text{Recall (Sensitivity)} = \frac{\text{TP}}{\text{TP+FN}} \quad (6)$$

$$\text{F1} - \text{Score} = 2 * \frac{\text{precision}*\text{recall}}{\text{precision+recall}} \quad (7)$$

TP represents True Positive, TN indicates True Negative, FP is an acronym of False Positive, FN represents False Negative.

TABLE I
PER-CLASS PRECISION, RECALL, AND F1 OF EEMK

Disease Class	Prec.	Rec.	F1
Leaf Blast	98.12	98.40	98.26
False Smut	98.64	98.20	98.42
Neck Blast	96.10	95.80	95.95
Sheath Blight	97.83	97.50	97.66
Bacterial Stripe	97.40	97.10	97.25
Brown Spot	96.98	96.85	96.91
Macro Avg.	**97.52**	**97.31**	**97.41**

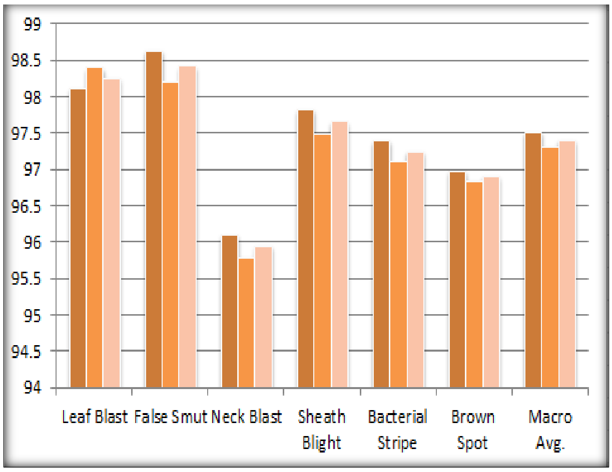

Fig 3: Performance Measures

TABLE II
ABLATION STUDY: IMPACT OF EEMK COMPONENTS

Method Used	Accuracy (%)
Random Forest	75.00
VGG-16(CNN)	91.99
Inception V3	88.39
Decision Tree	85
EEMK	97

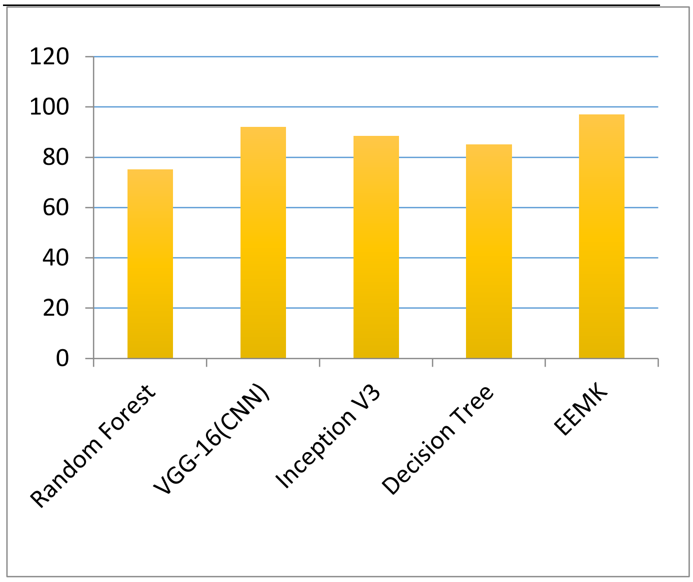

Fig 4: Comparison of Accuracy

V CONCLUSION

Lastly, combining drone-sensed aerial images and leaf images taken from the ground via a multi-view fusion component would facilitate field-level mapping of disease spread instead of identifying individual plants. The emergence of vision Spatial dependency modeling through Transformers (ViT) and efficient versions of these architectures (DeiT, Swin Transformer), which can model dependencies that convolu- tional receptive fields simply cannot represent, make the use of these technologies in the MFK approach extremely promising. Lastly, the adaptation of the mobile component to enable fully offline operation in IoT field sensors that may even be solar-powered trap cameras placed along field borders would extend the scope of this system to situations where access to a mobile phone device is limited or impossible. However, several research opportunities exist for further exploration. For instance, EEMK currently classifies diseases based on whether they are present or not in a particular plant. Extending the model to classify continuous classes of severity levels, such as mild, moderate, and severe diseases, will inform the optimal timing of pesticide application and loss estimation. Moreover, since the images used by EEMK were collected from locations within southern Karnataka, it is imperative to gather data from different geographical areas where rice crops are grown, including the Gangetic plain, the Mekong delta, and sub-Saharan Africa. In addition, the use of multiple views by fusing both drone-captured aerial images and leaf-level pho- tographs will be crucial for achieving field-level monitoring of diseases. Lastly, incorporating self-attention mechanisms in the form of transformers, which have proven effective in modeling spatial dependencies over long distances, into the multi-feature kernel architecture can revolutionize the system's performance. Notably, unlike convolutional receptive fields, vision transformers like ViT, DeiT, and Swin transformer can learn global contextual information across all input pixels. Finally, developing an offline mobile version of the system that runs on solar-powered IoT connected trap cameras installed at the periphery of the farms can address limitations in smartphone access.

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