Journal of Theoretical and Applied Information Technology
28th February 2025. Vol.103. No.4

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

FAST MASK REGION AND ENTROPY BASED HISTOGRAM EQUALIZED SEGMENTATION OF RICE PLANT DISEASES

MR. S. KOKILA[1], DR. S. ABIRAMI[2], DR. D. NAGARAJU[3]

1 Research Scholar, Department of CSE, Annamali University
2 Assistant Professor, Department of CSE, Annamali University
3 Professor, Department of CSE, Sri Venkateswara Perumal College of engineering &Technology.
1kokila.s521@gmail.com ,2reachabisv@gmail.com,3raj2dasari@gmail.com

ABSTRACT

The most common use of image processing nowadays is in the process of improving images. Conventional contrast enhancement approaches, which including Histogram Equalization (HE), have shown low performance on a wide range of low contrasted image, and are unable to handle various images automatically. These issues arise as a consequence of manually defining characteristics in order to obtain high contrasting images. In this paper, Fast mask Region and Entropy based Histogram Equalized (FMR-EHE) segmentation is proposed. In this research, Entropy based histogram is combined with Fast Mask Region segmentation to improve the accuracy of detecting and classification of Rice Plant Diseases. The proposed technique achieves many objectives, including keeping contrast, conserving the structural properties of the actual histogram, and adjusting the enhancement level. The simulation outputs demonstrate that the proposed method outperforms the published methods in terms of Mean Squared Error (MSE), Peak Signal-To-Noise (PSNR), and entropy calculation.
Keywords: *FMR-EHE, Histogram Equalization, Mean Squared Error, Rice Plant Diseases.*

1. INTRODUCTION

Rice is a significant crop which is grown for food in India and has a significant part in the country's economy. The output of rice needs to be ramped up in order to satisfy this demand. A wide variety of rice-specific illnesses are responsible for significant losses in crop production every year around the globe. The precise and timely prediction of the many diseases that might affect rice plants has been a significant obstacle for both farmers & researchers [1]. Techniques like as image capture, image processing, image segmentation, feature extraction, and ML are used in the autonomous leaf disease detection system used in precision agriculture. The farmer may get a prompt and accurate diagnostic of the plant illness with the assistance of an advanced disease detecting system [2].

Agriculture is the primary provider of food, clothing, and shelter for a significant portion of the world's population. In addition to this, it results in the creation of a significant number of new employment in the region. Farmers are to blame for decreasing crop yields since they continue to use agricultural techniques that are centuries old [3]. In the realm of agriculture, there has been a significant growth in the amount of research conducted on the identification of plant diseases through plant pictures that are based on machine learning. This might be accomplished by using pictures of rice plants (Oryza sativa L.) that have been infected [4]. Alterations in the conditions of the atmosphere are responsible for corresponding shifts in the temperature and condition of the soil. The diagnosis of plant diseases is an important task that must get priority attention if agriculture and the economy are to experience productive growth [5]. The detection of plant diseases via the use of conventional techniques is a laborious task that requires a significant amount of effort, time, and specialized knowledge.

Infections of crops may be discovered and detected accurately, which may prevent the rotting of harvests. Automatic crop disease identification in the wild is a challenging problem for today's intelligent agriculture because of the variety of symptoms that might be caused by crop diseases and the congested environment in which they occur. In agriculture, the loss of crop yield owing to organisms of living & non-living, known as biotic & abiotic stress and disease, accounts for around 22% of the total [6]. Farmers have a significant challenge when it comes to the detection of these pressures at an early stage using just their bare eyes. It is possible to identify the pattern and grouping of illnesses at an earlier stage by using computer vision technology.

Scientific in the subject of agriculture that focuses on the early diagnosis and diagnosis of plant diseases based on photographs of leaf lesions presents a significant and difficult research challenge [7]. Although agriculture is part of the primary sources of revenue in India, which provides 17 % of the overall gross domestically product, there is a necessity in the country for research studies of this sort to be carried out. Since the beginning of human history, agriculture has provided the major means by which people have supported themselves [8]. Plant diseases are responsible for a significant portion of the annual agricultural production losses that occur all over the globe. If you want to avoid incurring financial losses due to plant illnesses, it is essential to maintain the plants' health throughout the many phases of their growth and development [9]. The importance of agricultural growth in the economics of a nation is highly essential and should not be overlooked. However, the presence of a number of plant diseases is a significant barrier to both the pace of crop development and the quality of the produce.

The manual diagnosis of plant leaf infections by trained specialists based on visual observations is a time-consuming and error-prone process that raises concerns about the reliability of the results. The problems of time, effort & precision are the targets of an automated method, and their purpose is to solve these issues [10]. Agriculture continues to play a significant role in the economy of Morocco, accounting for around 15% of the country's total annual domestic product. Disease outbreaks are a persistent danger to the agricultural sector and result in significant financial losses for the nation. The health of plants as well as an accurate and early detection of plant diseases is of utmost significance for both the well-being of humans and the financial well-being of farmers all over the globe.

2 RELATED WORKS

It is very necessary to automate the system that detects plant leaf diseases in order to speed up crop diagnostics. The mean filtration is used in order to remove ambient noise from the signal. Histogram equalization is utilized as a means of improving the image's overall quality [11]. It contributes to the process of determining the limits of the image. K-Means is the method that is used in order to successfully segment the image. Image processing methods have recently benefited from breakthroughs in CNNs, which have made these methods more practical and accurate [12]. According to the results of the empirical research, the suggested model is able to accurately detect illnesses that affect rice plants with an accuracy of 97.3 % during validating with 96.3 % during testing, while having a model size that is much more compact.

The IoT and several methodologies based on ML have made it feasible to practice intelligent agriculture. The objective of this study [13] is to provide a methodology for the categorization of agricultural photographs in real time. Brown spot, bacterial leaf blight, & rice blast are three of the rice plant diseases that need to be eradicated in order to realize the greatest possible increase in crop yield [14]. The area and size of the infected sections are used to calculate the form characteristics that are taken from them. A new strategy to detecting and distinguishing apple leaf disease was developed by fusing suggested DWT & color histogram characteristics [15]. This approach achieved an accuracy of 98.63% in its detection and recognition of the illness.

The temperatures of the air and the soil each play unique roles in the development of crops, which may also cause illnesses to develop in rice plants. Experimentation on image processing with the use of machine learning algorithms are carried out in order to produce the prototype that is being suggested [16]. There is offered here an in-depth analysis of the several stages that must be completed in order to identify and categorize plant diseases using ML and deep learning. There are several datasets for plant disease detection that are accessible online, and some of them have been described [17]. The primary objective of this body of work [18] is to put into practice an innovative deep learning model for the categorization of agricultural diseases. During the phase of data collection, the benchmark dataset is used.

For the sake of item recognition and segmentation in this study [19], the PlantVillage dataset has been compiled. Data that has been tagged, enriched, and augmented has been used in the training of the model. There are many different algorithms, and they may be categorized according to their operating principles, such as edge-based, region-based, and combined properties [20]. The effectiveness of these algorithms was evaluated based on a number of criteria, including the amount of time needed, the accuracy, and the degree to which it resembled the original image.[21].

Therefore, feature extraction strategies are an extremely important component of such systems [22]. It offers an in-depth discussion on a wide range of image characteristics, including color, texture, and form, for a variety of illnesses that are prevalent in a number of different cultures. For the image of performance evaluation, a standard dataset known as the PlantVillage Kaggle along with the samples obtained through the use of a drone are used. This method is complicated due to the fact that the image samples are variable and the conditions under which they were captured are diverse [23].

The approach that is suggested in this work [24] is able to quickly, readily, and reliably identify disease occurrence regions, their species, and the degree to which the disease has damaged the rice crop. This provides a reference for disease management that is both timely and effective. The study [25] that is being presented investigates machine learning techniques for the purpose of disease diagnosis in various plant leaves. Experiments are performed using benchmark datasets provided by Kaggle and Mendeley respectively. A look into the future that has the potential to be a very helpful and beneficial reference for researchers [26] who are active in the area of agricultural disease identification.

A system that is powered by artificial intelligence (AI) is described in this study [27] in order to identify and categorize the most prevalent illnesses that affect guava plants. The efficiency of various several ensemble approaches in producing the best possible ensemble classifiers. The Plantvillage or Taiwan tomato leaf databases were used in order to evaluate the precision and resolution of the proposed technique in the lab and field environments, each of which presented its own unique set of obstacles [28]. Thus influenced by this idea, this paper [29] proposes a solution to use machine learning for identification of the disease in paddy plants. The system uses real time dataset obtained from the Agricultural Research Institute of Lonavala.

Chickpea disease is among the plant diseases that may affect plants. This disease is caused by fungi. The most prevalent forms of chickpea disease in Ethiopia, known as Ascochyta blight and Fusarium wilt, respectively, have a negative impact on both the quality and quantity of crop output [30]. The issue of overfitting was addressed by using augmentation, and 8391 photos were used for training and evaluating the performance of the newly constructed model.

3 PROPOSED METHODOLOGY

This section introduces the Fast Mask Region and Entropy based Histogram Equalized (FMR-EHE) segmentation algorithm. Entropy calculation is used in three stages: Threshold Value Segmentation, Contrast Image Segmentation, and Histogram Equalization are all examples of segmentation techniques as shown in fig 1.

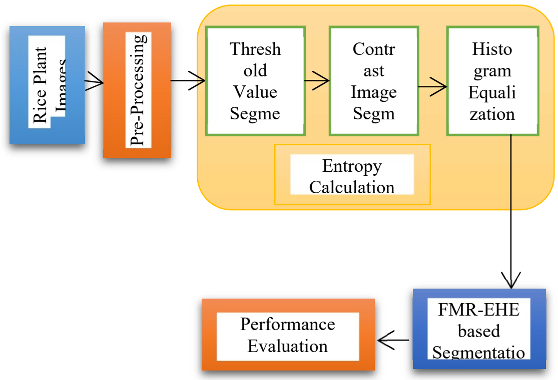

Figure 1: Overall architecture of FMR-EHE based Segmentation

The initial stage is to segment by Threshold Value. In reality, this step is quite useful in histogram segmentation and is successful in preserving brightness. The previous techniques of segmentation have not changed. As a result, the number of histogram bins exceeds the maximum number of levels and is limited to the threshold. (1) and (2) compute the average value:

$$Th = \frac{1}{M}\sum_{n=1}^{M} hist\ (n) \qquad (1)$$

$$hist\ (n) = Th \qquad (2)$$

Where hist(n) are the input & cropped histograms.

3.1 Fast Mask Region Neural Network

FMR-NN is a pixel-level image segmentation extension of Fast Region Convolutional Neural Network (FRCNN). It includes a third branched for displaying an object mask across the present FRCNN-based sections for classification and localization as shown in fig 2.

Because pixel-level segmentation requires much finer-grained connections than boundary boxes, FMR-CNN improves the RoI pool layer, allowing RoI to be enhanced and more correctly mapped to portions of the source image.

To calculate severe image exposure, a filter is used in the second stage. This phase divides the changed image into 2 sub-images: under/over exposed. The standardised sensitivity value range is [0-1]. If this quantity is more above 0.5, the image's major region is overexposed; if this quantity is less than 0.5, the image's most region is underexposed. In both circumstances, contrast enhancement must be performed. This value is written as

$$Exp = \frac{1}{M}\frac{\sum_{n=1}^{M} his\ (n)n}{\sum_{n=1}^{M} his\ (n)} \qquad (3)$$

Journal of Theoretical and Applied Information Technology
28th February 2025. Vol.103. No.4
© Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$PLow(k) = \frac{his(k)}{MLow} \quad (4)$$

$$PLow(k) = \frac{his(k)}{Mup} \quad (5)$$

$$Clow(k) = \sum_{l=0}^{a} PLow(k) \quad (6)$$

$$Cup(k) = \sum_{k=1}^{M-1} Pup(k) \quad (7)$$

Where $NLow$ and NUp are the no. of pixels in images $ILow$ & IUp. Individual images are subjected to equalization. The transfer functions for histogram equalization are as follows:

$$FLow = a \times Clow \quad (8)$$

$$FUp = (a+1) + (m-a+1)CUp \quad (9)$$

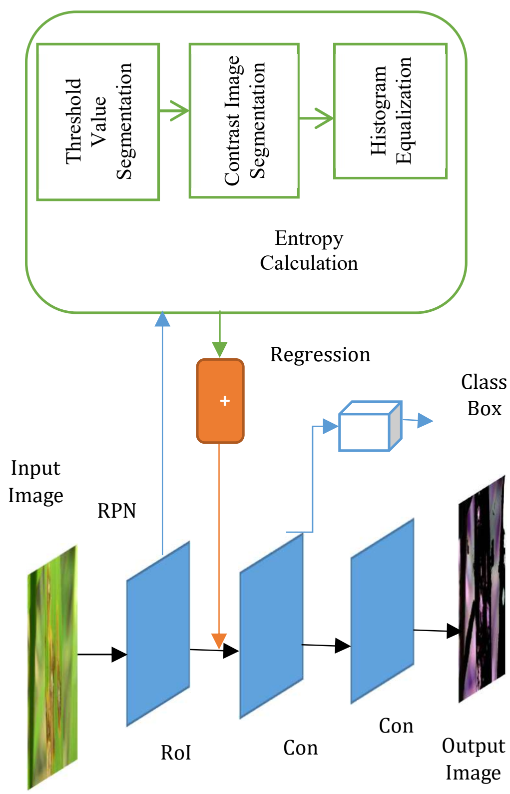

Figure 2. FMR-EHE Architecture

Algorithm 1: FMR-EHE Segmentation

Begin
Choose each individual element of the image.
Analyze each and every image.
while hist(n) = Th
do
removing entropy from the overall collection of entropy that is present
determine the entropy value of the image.
endif
endwhile
end
Choose each individual histogram element in the image.
examine
while hist(n) = Th
If the level of entropy is at its highest, delete the voxel.
for every histogram shown in the image

$$Exp = \frac{1}{M}\frac{\sum_{n=1}^{M} his\ (n)n}{\sum_{n=1}^{M} his\ (n)}$$

do
Determine an estimate for each histogram's entropy value in each element

$$FUp = (a+1) + (m-a+1)CUp$$

endif
endfor
endwhile
end

RoIAlign

The RoIAlign layer's purpose is to correct the location misalignment produced by quantization in RoI pooling. RoIAlign reduces hash quantization. The floating-point position variables in the input are computed via bilinear interpolation as shown in fig 3.

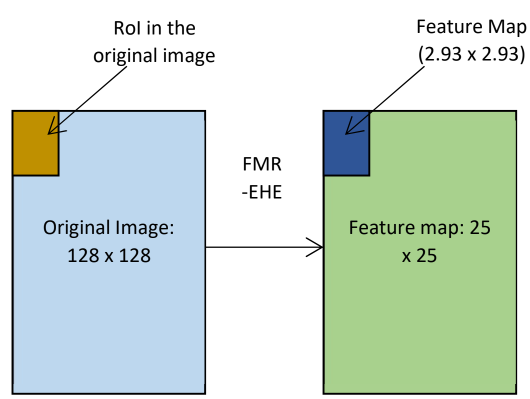

Figure 3. Feature Map using FMR-EHE

Entropy is added to evaluate the functionality of FMR-EHE. It is some of the measures used to determine image quality in order to assess improved images.

$$Entropy\ Image = -\sum_{M=0}^{M-1} P(k) \log p\ (k) \qquad (10)$$

Furthermore, entropy is calculated in bits and may be used as a criterion of image detail abundance. This entropy, known as Shannon Entropy, evaluates the uncertainty associated with an image's grey levels. The increased entropy indicates that the improved image has excellent quality and detail richness.

4 RESULTS AND DISCUSSION

4.1 Performance metrics

The suggested FMR-EHE Segmentation model's performance is measured using metrics such as True Negative Rate (TNR) and True Positive Rate (TPR), and accuracy.

Accuracy: As shown in equation, accuracy improves the accuracy of the classifier's categorization.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \qquad (11)$$

TPR: It quantifies the positive samples accurately recognized by the suggested FMR-EHE stated in equation.

$$TRP = \frac{TP}{TN + FP} \qquad (12)$$

TNR: It quantifies the negative samples that were appropriately rejected by the suggested FMR-EHE in equation.

$$TNR = \frac{TN}{TN + FP} \qquad (13)$$

4.2 Loss Function

FMR-EHE multi-task loss function includes the drop of classification, localization & segmentation masks, much as Faster R-CNN.

$$exp\_loss = 1/m * sum\left(exp\left(-y * f(x)\right)\right) \qquad (14)$$

The mask branch creates a m x m mask for each RoI and class; K classes in total. As a result, the overall output is of size. Because the model is attempting to generate a mask for every class, there is no rivalry for producing masks among classes.

4.3 Simulation Results

Following the segmentation procedure, the outside section is assessed for feature extraction. In reality, even pixels set to zero are taken into account when computing feature values that vary greatly from the true ones. To address this issue, we developed a new technique for generating the feature that makes use of the previously computed binary mask, enabling us to determine the amount of background pixels and eliminate them in the histogram & feature computation. Figure 4 shows the input image for the proposed FMR-EHE segmentation technique.

Figure 4: Rice plant input

Figure 5 shows the estimated entropy for an input image after passing it via Threshold Values for component identification in input image sequences.

Figure 5: Image using Entropy Estimation

To identify diseases in rice plants by utilizing one distinct sample as validity data and the rest k 1 samples as training data every time. Once the estimation of instances indicated by the classification models is produced, performance may be evaluated by compared it to the true class of instances, which in this case is the class suggested by the segmentation model. Figure 7 depicts a backdrop estimated image for illness identification. Similarly, in Figure 8, the highlighted area for disease estimate

Journal of Theoretical and Applied Information Technology
28th February 2025. Vol.103. No.4

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

in rice plant and classified plant disease in figure 9 and figure 10 calculated MSE value is shown as follows.

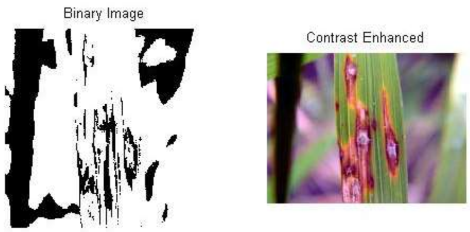

Figure 7: Normalized histogram using FMR

Figure 8: Histogram of FMR segmented segments

Figure 9: Classification of Plant Disease

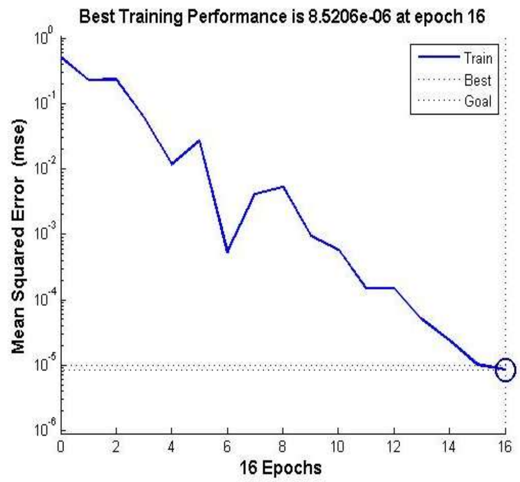

Figure 10. Mean Squared Error

For this specific challenge, characterized the occurrences as positive whenever the rice plants were impacted by illnesses and computed the efficiency value depending on this definition. Since accuracy is the more often used statistic, it gives equal weight to each class. The approximated entropy-based classification involves the calculation of proper positive instance categorization. The sensitivity value is utilized for this reason. The table shows the three times necessary for disease segmentation.

Table 3: FMR-EHE Segmentation Time

Image Dataset	Size in Pixels	Segmentation Time
1	160 x 210	10.58
2	210 x 240	12.46
3	240 x 300	11.82
4	154 x 220	8.2
5	220 x 240	12.86

The segmentation frequency evaluated for the suggested FMR-EHE with various dataset pictures is provided. According to the findings, the suggested FMR-EHE has the shortest segmentation time for identifying illnesses in rice plants. Table 4 compares the TPR determined for the proposed FMR-EHE to current approaches. Figure 11 shows a comparison of TPR with current approaches.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 4: TPR analysis for various validations

Iterations	NN	SVM	KNN	Random Forest	CNN	RCNN	FRCNN	Proposed FMR-EHE
1	61	62	64	69.4	72.7	78	82.6	86
2	63	65	69.7	74	79	80	87	89
3	66	72	76	78	83	84	85	89
4	69	75	80	84.6	86	87	88	90
5	75	79	81.6	84.2	88	88	89	91

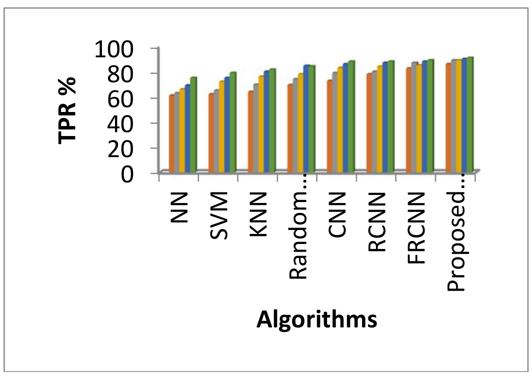

Figure 11: TPR Comparison

Among known techniques, FRCNN outperforms CNN, SVM, KNN, Random Forest and RCNN. The suggested FMR-EHE, on the other hand, outperforms current approaches. TNR comparison is shown in table 5.

Table 5: TNR analysis for various validations

Iterations	NN	SVM	KNN	Random Forest	CNN	RCNN	FRCNN	Proposed FMR-EHE
1	56.8	58	61.2	71.2	77	83	85	89
2	53	61.6	66	74	76	84	86	87
3	55.6	67.3	70	76	81	86	87	88
4	57.8	74.2	75	77	80.6	85.5	88	89
5	58.8	80	83	85	86	88	89	90.2

TNR is compared in Figure 12 for proposed FMR-EHE with current NN, SVM, KNN, Random Forest, CNN, RCNN, and FRCNN.

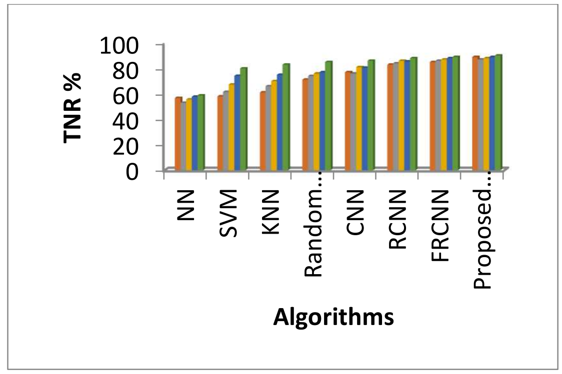

Figure 12: TNR Comparison

According to the results analysis, the suggested FMR-EHE delivers a greater TNR rate than the present approach. According to the comparison study, estimating image entropy improves the segmentation precision of the proposed FMR-EHE. Table 6 compares the accuracy of the proposed FMR-EHE to current approaches. Figure 13 depicts a comparison of the proposed FMR-EHE with the present approach.

Table 6: Accuracy analysis for several validations

Iterations	NN	SVM	KNN	Random Forest	CNN	RCNN	FRCNN	Proposed FMR-EHE
1	45	49	53	62	69	71	74	79
2	52.34	56.2	61	65.7	71.34	73.65	77.26	80
3	64.2	66	63.60	68.5	74.63	81.26	82	84.6
4	65	69	67.29	70.83	78.49	88	83	89
5	69	70	71.2	73.6	81.1	86.3	85	90.6

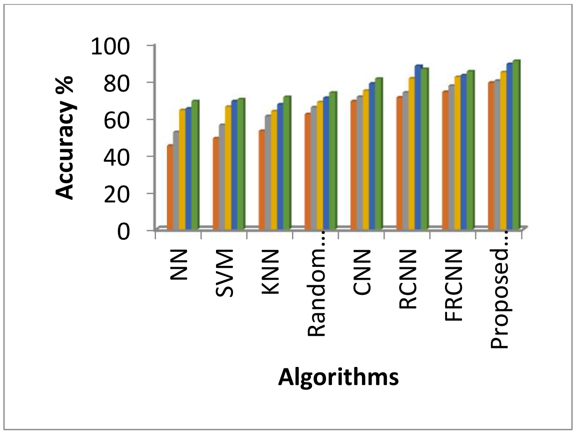

Figure 13: Comparison of Accuracy

The suggested FMR-EHE accuracy evaluation is much greater than current methodologies, according to the comparison study. The suggested FMR-EHE employs entropy to reduce distortions and histogram equalization to calculate component variation, resulting in increased accuracy of the proposed FMR-EHE. Table 7 shows an overall comparison of the proposed FMR-EHE with NN, SVM, KNN, RF, CNN, RCNN, and FRCNN.

NN, SVM, KNN, RF, CNN, RCNN, and FRCNN yield efficiency of 58.2%, 63.02%, 62.3%, 69.23%, 75.8%, 81%, and 81.36%, respectively. The suggested FMR-EHE, on the other hand, has an accuracy value of 84.64%, which is roughly 4% higher than the previous approach. Figure 14 depicts a comparative examination of the proposed FMR-EHE in contrast to the existing.

Table 7: Overall Comparative Evaluation

Procedures	Coefficient of Dice	Percentage of TPR	Percentage of TNR	%
NN	78.63	67.9	57.5	58.2
SVM	78.15	72.5	69.21	63.02
KNN	82.35	75.3	72.3	62.3
Random Forest	82.65	79.02	78.63	69.23
CNN	83.53	82.8	81.23	75.8
RCNN	85.91	94.3	85.3	81
FRCNN	82.26	85.2	88	81.36
Proposed FMR-EHE	87.69	88	87.6	83.65

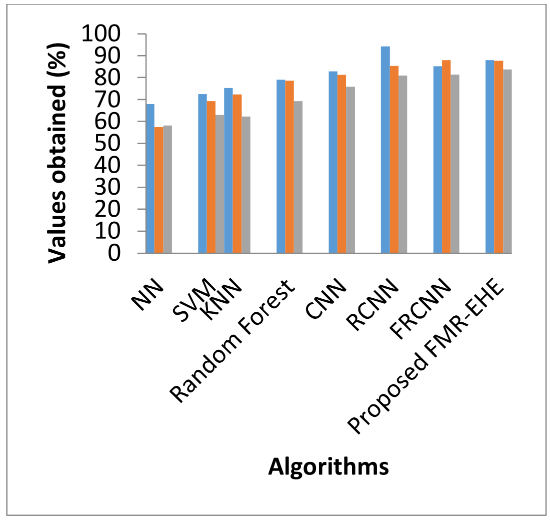

Figure 14: Overall Evaluation

The suggested FMR-EHE approach is compared to current techniques using greater values. The suggested FMR-EHE outperforms current NN, SVM, KNN, Random Forest, CNN, RCNN, and FRCNN in terms of TPR, TNR, and accuracy. The research indicated that the suggested FMR-EHE performs better.

5 CONCLUSION

The FMR-EHE classification system was proposed. In this research, the Entrophy-based histogram is combined with FMR segmentation in order to improve the accuracy of detecting as well as classifying diseases that affect rice plants. The method that was provided was successful in accomplishing various goals, such as maintaining the contrast of the image, preserving the structural characteristics of the actual histogram, including modifying the enhancement rate. The results of the simulation show that the proposed method is superior to the conventional approaches with regard to Mean Squared Error (MSE), Peak Signal-To-Noise (PSNR), and entropy calculation. According to the results of the analysis, the recommended FMR-EHE performs more effectively.

REFERENCES:

1. Atila, Ü., Uçar, M., Akyol, K., & Uçar, E. (2021). Plant leaf disease classification using EfficientNet deep learning model. *Ecological Informatics*, *61*, 101182.
2. Lu, J., Tan, L., & Jiang, H. (2021). Review on convolutional neural network (CNN) applied to

plant leaf disease classification. *Agriculture*, *11*(8), 707.
3. Azim, M. A., Islam, M. K., Rahman, M. M., & Jahan, F. (2021). An effective feature extraction method for rice leaf disease classification. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *19*(2), 463-470.
4. Wang, C., Du, P., Wu, H., Li, J., Zhao, C., & Zhu, H. (2021). A cucumber leaf disease severity classification method based on the fusion of DeepLabV3+ and U-Net. *Computers and Electronics in Agriculture*, *189*, 106373.
5. Thangaraj, R., Anandamurugan, S., & Kaliappan, V. K. (2021). Automated tomato leaf disease classification using transfer learning-based deep convolution neural network. *Journal of Plant Diseases and Protection*, *128*(1), 73-86.
6. Sujatha, R., Chatterjee, J. M., Jhanjhi, N. Z., & Brohi, S. N. (2021). Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocessors and Microsystems*, *80*, 103615.
7. Nandhini, S., & Ashokkumar, K. (2021). Improved crossover based monarch butterfly optimization for tomato leaf disease classification using convolutional neural network. *Multimedia Tools and Applications*, *80*(12), 18583-18610.
8. Chowdhury, M. E., Rahman, T., Khandakar, A., Ayari, M. A., Khan, A. U., Khan, M. S., ... & Ali, S. H. M. (2021). Automatic and reliable leaf disease detection using deep learning techniques. *AgriEngineering*, *3*(2), 294-312.
9. Chouhan, S. S., Singh, U. P., Sharma, U., & Jain, S. (2021). Leaf disease segmentation and classification of Jatropha Curcas L. and Pongamia Pinnata L. biofuel plants using computer vision based approaches. *Measurement*, *171*, 108796.
10. Khalifa, N. E. M., Taha, M. H. N., El-Maged, A., Lobna, M., & Hassanien, A. E. (2021). Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach. In *Machine Learning and Big Data Analytics Paradigms: Analysis, Applications and Challenges* (pp. 63-79). Springer, Cham.
11. Zamani, A. S., Anand, L., Rane, K. P., Prabhu, P., Buttar, A. M., Pallathadka, H., & Dugbakie, B. N. (2022). Performance of machine learning and image processing in plant leaf disease detection. *Journal of Food Quality*, *2022*, 1-7.
12. Prottasha, S. I., & Reza, S. M. S. (2022). A classification model based on depthwise separable convolutional neural network to identify rice plant diseases. *International Journal of Electrical & Computer Engineering (2088-8708)*, *12*(4).
13. Nancy, P., Pallathadka, H., Naved, M., Kaliyaperumal, K., Arumugam, K., & Garchar, V. (2022, March). Deep Learning and Machine Learning Based Efficient Framework for Image Based Plant Disease Classification and Detection. In *2022 International Conference on Advanced Computing Technologies and Applications (ICACTA)* (pp. 1-6). IEEE.
14. Archana, K. S., Srinivasan, S., Bharathi, S. P., Balamurugan, R., Prabakar, T. N., & Britto, A. S. F. (2022). A novel method to improve computational and classification performance of rice plant disease identification. *The Journal of Supercomputing*, 1-21.
15. Hasan, S., Jahan, S., & Islam, M. I. (2022). Disease detection of apple leaf with combination of color segmentation and modified DWT. *Journal of King Saud University-Computer and Information Sciences*, *34*(9), 7212-7224.
16. Kumar K, K., & E, K. (2022). Detection of rice plant disease using AdaBoostSVM classifier. *Agronomy journal*, *114*(4), 2213-2229.
17. Wani, J. A., Sharma, S., Muzamil, M., Ahmed, S., Sharma, S., & Singh, S. (2022). Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges. *Archives of Computational Methods in Engineering*, *29*(1), 641-677.
18. Farooqui, N. A., Mishra, A. K., & Mehra, R. (2022). Concatenated deep features with modified LSTM for enhanced crop disease classification. *International Journal of Intelligent Robotics and Applications*, 1-25.
19. Kaur, P., Harnal, S., Gautam, V., Singh, M. P., & Singh, S. P. (2022). Comparative Analysis of Segmentation Models to Detect Leaf Diseases in Tomato Plant.
20. Hassan, S. M., Amitab, K., Jasinski, M., Leonowicz, Z., Jasinska, E., Novak, T., & Maji, A. K. (2022). A Survey on Different Plant Diseases Detection Using Machine Learning Techniques. *Electronics*, *11*(17), 2641.
21. Jadhav, S., & Garg, B. (2022, September). Comparative Analysis of Image Segmentation Techniques for Real Field Crop Images. In *International Conference on Innovative Computing and Communications: Proceedings*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

of ICICC 2022, Volume 2 (pp. 1-17). Singapore: Springer Nature Singapore.

22. Vishnoi, V. K., Kumar, K., & Kumar, B. (2022). A comprehensive study of feature extraction techniques for plant leaf disease detection. *Multimedia Tools and Applications*, 1-53.
23. Albattah, W., Javed, A., Nawaz, M., Masood, M., & Albahli, S. (2022). Artificial intelligence-based drone system for multiclass plant disease detection using an improved efficient convolutional neural network. *Frontiers in Plant Science*, *13*.
24. Li, Z., Chen, P., Shuai, L., Wang, M., Zhang, L., Wang, Y., & Mu, J. (2022). A Copy Paste and Semantic Segmentation-Based Approach for the Classification and Assessment of Significant Rice Diseases. *Plants*, *11*(22), 3174.
25. Minz, S. (2022). Disease Detection of Plant Leaves with the Aid of Region Growing and Neural Network: A Comparative Analysis. In *Advanced Machine Intelligence and Signal Processing* (pp. 281-298). Singapore: Springer Nature Singapore.
26. Orchi, H., Sadik, M., & Khaldoun, M. (2022). On using artificial intelligence and the internet of things for crop disease detection: A contemporary survey. *Agriculture*, *12*(1), 9.
27. Almadhor, A., Rauf, H. T., Lali, M. I. U., Damaševičius, R., Alouffi, B., & Alharbi, A. (2021). AI-driven framework for recognition of guava plant diseases through machine learning from DSLR camera sensor based high resolution imagery. *Sensors*, *21*(11), 3830.
28. Astani, M., Hasheminejad, M., & Vaghefi, M. (2022). A diverse ensemble classifier for tomato disease recognition. *Computers and Electronics in Agriculture*, *198*, 107054.
29. Sequeira, I., Shah, S., Sengupta, S., Mathurvaishya, E., Waykole, C., & Raghuwanshi, K. S. (2022). AgriCare: To detect and prevent paddy crop diseases using machine learning. *Available at SSRN 4108881*.
30. Belay, A. J., Salau, A. O., Ashagrie, M., & Haile, M. B. (2022). Development of a chickpea disease detection and classification model using deep learning. *Informatics in Medicine Unlocked*, *31*, 100970.