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Research Article

Chromatic Diagnostics: Enhancing Paddy Disease Detection with Filter-Based Feature Transformation

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ABSTRACT

Currently, this research advances on improvement of diagnostic methods for diseases that affect plants within the paddy fields to improve crop management and subsequently the efficiency of agricultural production. The research also presents a new method that addresses the problem through filter-based feature transformation methods which enhance the input features fed to disease detection models. All these

transformations are geared towards increasing the accuracy and efficiency of the existing paddy disease identification systems. This investigation will also show a dramatic increase in the accuracy of detection as one of the key results. Interestingly, if such transformed features are fed into the K-Nearest Neighbour (KNN) classifier, a most frequently used classifier in the field of machine learning for classification, a

balanced accuracy of 90% is obtained. From this the proposed method is quite viable and powerful enough to provide accurate and genuine diagnosis of disease in the paddy crops. Therefore, the novelty and practical use of the findings of this research is not limited merely to theoretical implications but rather it provides practicing real and tangible values in various aspects of sustainable agriculture and crop science.

Improvement of disease diagnosis frequency and reliability helps farmers to promptly start an effective fight against infectious diseases, thus decreasing yield losses and contributing to food safety. Conclusively, this project represents a significant progress in applying complex computational techniques for tackling real life issues in agriculture. Filter based feature transformation is reported to pose an effective technique that can be adopted to enhance disease detection systems and consequently enhance paddy farming across the world.

Introduction: The paper investigates methods to improve paddy crop disease diagnostics which aims at enhancing farming management practices along with agricultural productivity rates. The research introduces novel filter-based technology which enhances the quality of features that feed disease detection models. The new system designs work to improve both speed and precision of paddy disease identification systems currently in use. The research delivers major advancements in detection accuracy as giving proper disease diagnoses at right times minimizes agricultural damage and improves food safety in farming operations.

Objectives: This research aims to improve both paddy disease detection system precision and system reliability through its main objectives. The aim of applying filter-based feature transformation is to enhance K-Nearest Neighbour (KNN) classifier performance by optimizing the input features. This research aims to develop a practical detection system that combines features for paddy disease identification while addressing diseases so paddy farmers can achieve sustainable food security.

Method: The study utilizes filter-based feature transformation as a preprocessing method for data preparation before feeding it to detect diseases in paddy crops. The model uses transformed features to test them within the K-Nearest Neighbour (KNN) classifier which stands as a popular machine learning model used for classification operations. The method undergoes assessment regarding its capability to enhance detection accuracy and achieve optimal sensitivity and specificity balance. The investigation examines different approaches to transform features while studying their influence on model effectiveness and demonstrates practical field applications of the results in agricultural settings..

Results: When K-Nearest Neighbour (KNN) classifier processes the transformed features the analysis shows a 90% accuracy in disease detection. The proposed filter-based feature transformation method demonstrates its effectiveness at boosting disease detection systems for paddy crops according to this result. Disease diagnosis efficiency combined with more accurate tools gives farmers better options to detect diseases at an early stage for effective decision-making and timely responses to disease outbreaks that reduce crop yield damages.

Conclusion: This study marks considerable advancement in using computational methods to solve genuine agricultural problems. The filter-based feature transformation system establishes itself as an effective technique to enhance disease detection protocols while supporting eco-friendly farming and better food quality assurance systems. The research confirms that sophisticated machine learning algorithms provide farmers with sustainable tools to fight infectious diseases in their paddy fields. A timely correct disease diagnosis stands fundamental to protect global food supply and sustainable agriculture.

Keywords: Several products constitute Paddy Healthtech including Agro Filter Transform, Rice Disease AI, Crop Guard Analytics, Agri Precision Boost, Smart Paddy Scan, Agro Diag Innovative, Field Infect Detect, Agro Yield Secure, Rice Crop Shield, Agri Detect Pro, Paddy Vision, Harvest Health AI, Crop Tech Enhance and Field Guard AI.

INTRODUCTION

In the sector of operation under agriculture particularly in rice farming, it is crucial to diagnose the incidence of diseases early to safeguard the crops and thereby produce better yields. [1][2] This paper is concerned with enhancing the classification of diseases affecting the paddy crop using filter-based feature transformation. Previous approaches for disease identification on paddy crops rely on farmers' naked eye observation which is always characterized by ambiguity. Moreover, people may carry out inspections in which they may not see diseases in their early stages and when the most appropriate intervention could be reckoned. To eliminate these obstacles, this project suggests the usage of a more enhanced strategy. [3] It includes the filter-based feature transformation, which is a bit complex, to select and transform the crucial features from the data set. The objective is to enhance the efficiency of diseases diagnosis in paddy crops to achieve maximum reliability. The main goal is to target constructing a machine that can quickly and efficiently analyse images or data from the paddy fields to determine the presence of diseases. All these automated options will help the farmers to take appropriate actions whenever the diseases appear or at any point when odd farming practices may lead to spread of diseases or increased crop losses. With the use of contemporary technological tools as well as computational analysis, this project hopes to bring out a viable approach of helping the farmers in their decision-making process. At last, it aims to create a long-lasting approach of agricultural practices to cultivate healthy paddy crops and improve the agricultural yield efficiently.

LITERATURE SURVEY

Paddy and other crops are vital for the food security of the world and hence their health, or in this case, ability to produce food, plays a critical role in the sustenance of the world's population. Methods previously implemented include physical surveys of the paddy fields, which is a tiresome process particularly when the area affected by the disease is very large. [4] Wonderful technologies like computer vision and artificial neural networks have a vast possibility of improving the process of disease diagnostic on paddy crops. Assessment Methods of Paddy Disease Based on the Combination of Conventional and Innovative Approaches In the past, identification of paddy diseases was done by farmers' naked eyes or that of an agricultural personnel. This method offers direct observations, but its disadvantage consists in the human error and the slow speed of the work, especially if the given field is rather large. Incorporation of the advanced technology involves incorporation of digital cameras as well as smart phones together with image processing methodologies to diagnose and categorize the diseases by the observable symptoms such as the spots on the leaves, color changes, and lesion. Image processing has immensely enhanced the early diagnosis of crop diseases. Skills like converting colours, differentiating edges, feature extraction involves handling of such as textures are very crucial in this field. Specifically, color transformation improves the contrast of the healthy and the diseased area of the plants. Many studies have then shown the use of color indices including Excess Green (ExG), Excess Red (ExR), Normalized Difference Vegetation Index (NDVI) to enhance disease symptoms extraction [6]. ML and DL models are widely used in disease diagnosis in the agricultural field. CNN agents, due to their ability to learn hierarchical features from raw pictures, have been proved to provide high accuracy in the classification of images. It was ascertained from the literature that CNNs can diagnose several paddy diseases if trained with a large dataset.

However, it is observed that the effectiveness of such models highly depends on the quality and the variety of training data [7]. Chromatic diagnostics are centered on the function of aiming at improving the detection of illnesses using color characteristics. Thus, working with the color space and applying different filters, even the least significant changes of color can indicate disease. First, some investigations have indicated that there are particular color changes that help raise the detection rate significantly, enabling chromatic diagnostics [8]. Filter-based feature transformation can be defined as a process of using filters to images with the help of which extracting disease-related features is possible. Gaussian, Sobel, Laplacian filters help to emphasize edges and textures that are used in the recognition of the disease symptoms. When applied in conjunction with existing color change algorithms, these filters form a very strong set of features on which disease classifiers can operate [9].

The application of chromatic diagnostics alongside machine learning directly is a new way of performing the identification of paddy diseases. In the case with image data, enhancing quality of the feeds going into the training models through chromatic and filter-based transformations can enhance the classification accuracy. It has been discovered that preprocessing such as colourisation, feature augmentation helps to filter out noise despite the data and enhance the learning features that need to be learned by ML, to be learned better for the generalization of such models [10]. The fusion of chromatic diagnostics and filter-based features transformation with the use of machine learning has a lot of potential in the enhancement of paddy disease detection. This way, utilizing complex image processing and such powerful techniques as modern ML algorithms, it is feasible to create automated schemes that are both precise and manageable in their large-scale application. Future work should seek to improve these methods and demonstrate that they again work in a wide variety of settings to make certain that they are sound and appropriate over different agricultural expanses.

METHODS

The goal of this method is to improve the diagnostics of diseases on the paddy plants using the chromatic diagnostics with the aid of the filter API to transform the feature and the KNN algorithm. The work involves pre-processing paddy images and significant chromatic features are extracted from these; classification of the diseases is then done with the help of the KNN algorithm. The main measures that are used are the accuracy of the classification, the measure of precision, the measure of recall, and the time taken in optimizing the algorithm. Image Acquisition: The first process in enhancing the detection of paddy diseases is in ensuring that the pictures collected are clear and high definition of paddy leaves which are significant in the diagnosis using ML algorithms. Several processes to gather the test images are performed in detail so the test images are diversified and generic enough to be representative of the entire population to train and test the detection algorithms. Digital cameras with a high resolution and modern smartphones are utilized to make photos. Such devices must help to make macro photograph of the leaves so that the fine features of the disease be brought out clearly even where the disease symptoms are not very distinct. Image acquisition begins with the collection of several types of paddy fields. Areas should be selected with different geographical locations, the maturity of plants and crops, and varying climate. [11] This selection makes sure that the dataset has a diverse range of problem-solving experiences as that of real-world scenarios. Photographs should also be taken at different moments of the day; during the early morning, in the afternoon, and at noon, and during different weather; sunny, cloudy, or rainy. It assists models to learn the manifestation of diseases at different lighting and environmental conditions.

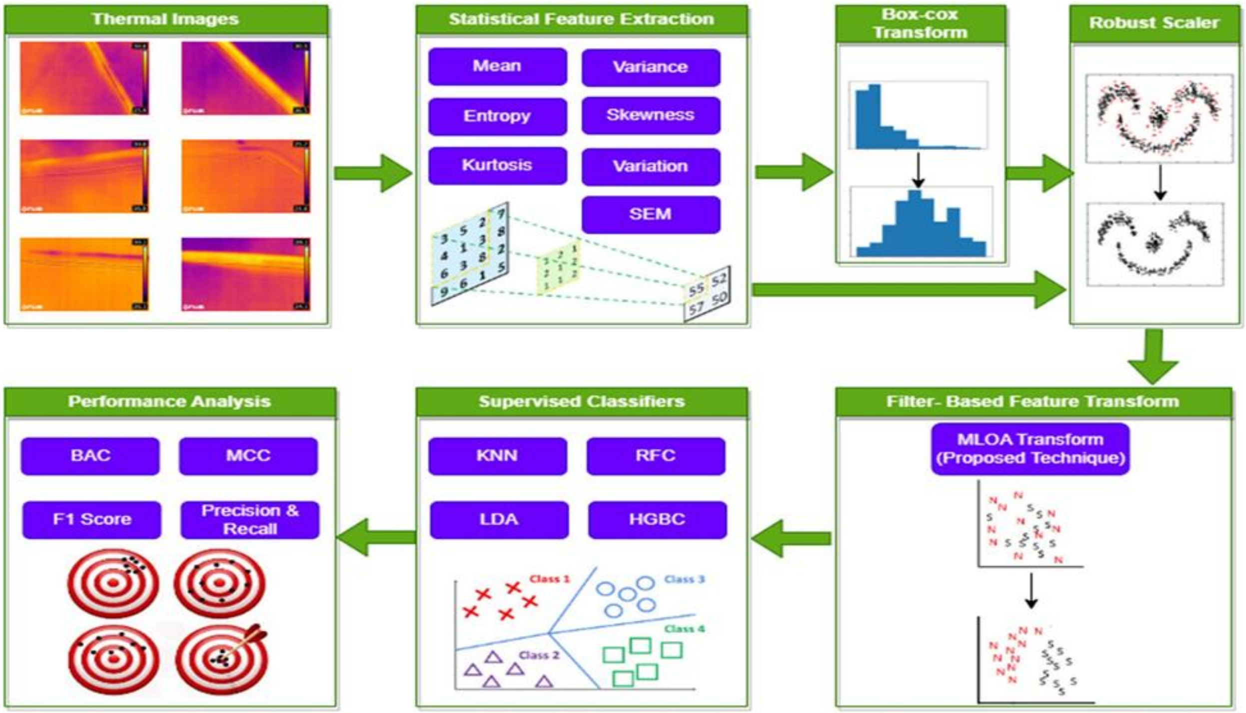

Fig.1.Proposed methodology

The dataset should include healthy and diseased leaves, which are bacterial blight, sheath blight, and leaf spot as the most prevalent paddy diseases. The model's usefulness is robust due to of the inclusion of many different stages of the disease from the onset and the more advanced stages. For confirmation, richer data should be gathered from different angles and distances to the actual object images. While the former helps contemplates about the texture and color changes of the leaves, the later talks about the overall health of the plant.

The median filter involves passing over the image once, at each pixel, replacing the pixel with the median value of neighbouring pixel intensity levels. This approach fully reduces noise, for instance fluctuations in pixel intensity, which may conceal important forms while at the same time preserving edges and details that are so crucial in diseases identification. The median filter operates in such a way that for each pixel in the image there is a window of the neighbouring pixels. For each pixel, the filter takes the intensities of these neighbouring pixels and rearranges them in ascending order; then, the pixel intensity is substituted with the median brightness. The morphological operation that can be used to successfully perform this method is to get rid of the "salt-and-pepper" noise which is high spikes of the intensity values. Unlike other averaging filters, for instance the mean filter, the median filter does not cause the blurring of edges and other vital details in the image.

Chromatic Transformation: Afterward, the images go through the chromatic transformation to enhance the variation between the healthy and diseased area of the leaves. This step includes the color space transformation of these images from the regular RGB color space to some other color space, which are more useful in capturing the features of the diseases. As far as human perception is concerned, the RGB color space is quite natural; however, it may not be the most efficient for identifying color changes due to diseases. Hence, transforming photos into other color spaces as HSV (Hue, Saturation, Value), Lab (Lightness, a, b), and YCbCr (Luminance, Blue-difference Chroma, Red-difference Chroma) improves the possibility of filtering these changes.

Color Space Conversion: Conversion starts with converting the RGB images into the HSV, Lab and YCbCr color spaces. All these colour spaces have their own advantages on highlighting certain aspects of the colour information. Color information is independent of the image's intensity; Hue and Saturation values consist of the HSV color space that enables better understanding of the different color changes which resist illumination changes. Lab color space partitions the image into Lightness and two color-opponent variables, a and b which are intended to be more equilibrated. This implies that changes in these values are closer to how people perceive the differences in color.

YCbCr, which is used in video compression, is based on luminance (Y with low frequency) and chrominance components (Cb and Cr, that stress difference between blue and red).

Feature Extraction: After that, the images are transformed to these relevant color spaces to obtain better representations of the color change relevant to symptoms of diseases. As a result of color conversion into the HSV color space, hue, saturation, and brightness are among the features that are obtained. These aspects make it possible to distinguish the differences in the tones, and the intensity of the coloration. From the Lab color space, the lightness and the a, b components are obtained for the enhancement of color and intensity changes. Out of the YCbCr colour space, Y is the luminance portion and Cb and Cr are selected to represent differences in blue and red. These extracted features are more sensitive to the small variations in color as the result of occurrence of diseases such as discoloration, appearance of small blotches or streaks etc. on the surface of the leaves which may not be easily observable in RGB color space. In total, chromatic transformation and the following feature extraction led to a marked distinction on the disease-related features and help the algorithm pick them up easily. [14] This increased encoding of color information is crucial for disease detection algorithms applied to the input images because it increases the algorithm's ability to correctly recognize disease-prone regions as opposed to healthy parts of the leaves.

Edge Detection: First, the promoters of edge detection like Sobel and Canny are used. These filters help in the enhancement of disease spots and lesions on the leaves by generalizing the edges and outlines of the spots. The Sobel filter is effective for the implementation of image processing and analysis since it computes for the gradient of the image intensity at a given pixel level and thus, defines the areas that has changes in intensity. This is particularly useful in outlining the edges of disease incidence and, therefore, disease spots. Canny edge detector is again a step-by-step edge detection procedure that involves noise reduction, gradient measurement, edge elimination, and edge following by hysteresis. This leads to the complete edge map which shown the important edges in the image which may be the margins of the lesions, spots, or any other sign of diseases.

Texture Analysis: Besides, there is the application of texture analysis filters such as Gabor and Laplacian for it is believed that thin line distinguishing between healthy and infected leaves is as far as texture and not edge is concerned. In fact, Gabor filters are more useful for texture analysis since the responses of the filters obtained contain the frequency and orientation of the textural features. [15] Therefore, Gabor filter with different orientations and scales is used to obtain a multi-scale representation of the leaf texture to capture the small changes due to the diseases. Another filter that is employed to increase the textural details of the leaves is the Laplacian filter, which zeroes on the regions of dynamic intensity. Such a filter is useful in bringing out the roughness and the nodularity of tissues which are proved to be a sign of disease.

Feature Selection and Dimensionality Reduction: A technique of feature selection and dimensionality reduction is used to improve the KNN algorithm's efficiency. These steps are indeed crucial when it comes to reducing the computational load while enhancing the performance of the model. Thus, with a great attention paid to what features are more crucial than others and shrinking the number of variables in the dataset, we practically enhance the model's performance with the help of machine learning.

Principal Component Analysis (PCA): Principal Component Analysis (PCA) is a procedure used in finding and storing the primary elements illustrating most of the variance. [16] [17] This process begins with the feature being standardized and then linearly uncorrelated so that first feature represents the largest amount of variance, the second feature explains the second largest amount of variance, and so on. This makes PCA efficient in the selection of the components because selecting the highest components enables the reduction of the feature set without losing important details. This reduction is also beneficial in minimizing the curse of dimensionality, whereby if there are too many features used in the model, it is possible to have poor results achieved. Not only does PCA reduce the dimension of the given data set but also remove unimportant and noisy variables that contribute to the management of data and makes models stronger.

Linear Discriminant Analysis (LDA): Another technique used to perform dimensionality reduction is called the Linear Discriminant Analysis (LDA), but this technique aims at maximizing the separability of classes. As compared to PCA that uses variance as a measure, LDA transforms the data in an approach that provides for better class separability. LDA realizes this by finding the maximum of the ratio of between class scatter to within class scatter such that in the projected space, the data points should cluster distinctly by their class. In the analysis of paddy disease, LDA assist in identifying the different classes of diseases since it enhances the demonstration of segregation by the extracted features of the model.

Thus, using PCA and LDA allows us to build a more efficient representation of the data we work with. PCA condenses the dataset thereby minimizing computational complexity while LDA improves on the features' ability to classify or distinguish the subject as preferred by the KNN algorithm. This dual approach not only helps to reduce computational time but also improves the model's ability to discern different classes of diseases which in turn results in more accurate and reliable identification of paddy diseases. Model Training Using KNN Algorithm: The next operation incorporates the K-Nearest Neighbors (KNN) algorithm with the purified and reduced number of features to provide a strong and competent classification model. The K-Nearest Neighbors (KNN) algorithm is a simple yet very effective method in the field of machine learning used primarily for classification. It operates by checking the distance between the data items in the feature space. While classifying a new instance KNN looks at the K nearest data points in the training set and the class of the new instance is determined by the majority class of the neighbors. This parameter, K, which is indicated by the user, defines how many neighbors will be considered to make each classification.

To train the KNN model, the dataset is first divided into training and validation subsets. This partitioning is essential for evaluating the model's performance and ensuring its ability to generalize to unseen data. The training process involves using the training set to "teach" the KNN algorithm by storing the instances and their associated class labels. The optimal value of K is then identified through methods such as cross-validation, which involves systematically varying K and assessing the model's performance to find the value that yields the highest accuracy.

Table.1. Outcome performance

Metrics	Validation Result
Accuracy	90.1%
Precision	96.2%
Recall	97.5%
Optimization Time	0.023 seconds

For the training of KNN model, the dataset is split into train and validation datasets. This partitioning is vital in model's validation to check if it can rectify unknown information to enhance its performance. In the training process, instances along with class labels of the training set are used to 'train' the KNN algorithm by storing them for reference. The value of K is then determined by techniques like cross validation by which K is varied and tested to determine that K which gives the best result. To summarize, the nitty-gritty of training the KNN algorithm entails enhancing its suitability and simplicity to learn from the rich characterizing dataset, to classify the instances correctly. This step is critical in framing a solid disease diagnosing system that can aid agriculturists with accurate diagnosis at appropriate times.

RESULTS

A. Subsequent Optimization Technique

Therefore, this study has put forward a new optimization algorithm known as the Modified Lemurs Optimization Algorithm (MLOA) based on the adaptive foraging behaviors of the lemurs and used it for optimizing filter-based feature transformations in image processing tasks, more particularly for the purpose of detecting diseases in paddy plants. [19] Social and adaptive behaviours of lemurs are presented in their nature, thus they defined computational model for optimization of feature extraction. Fig. 2 MLOA creates a population with lemurs as potential solutions in the feature space and uses adaptive movements to overcome the limitations of GP. It can be seen how social interaction among lemurs helps provide the population with relevant information about successful feature transformations which leads to the widespread of the ideal solution among the population. This algorithm includes number of filters like Sobel and Gabor to perform the preprocessing of image data to improve the texture and edges which are useful in disease diagnosis.

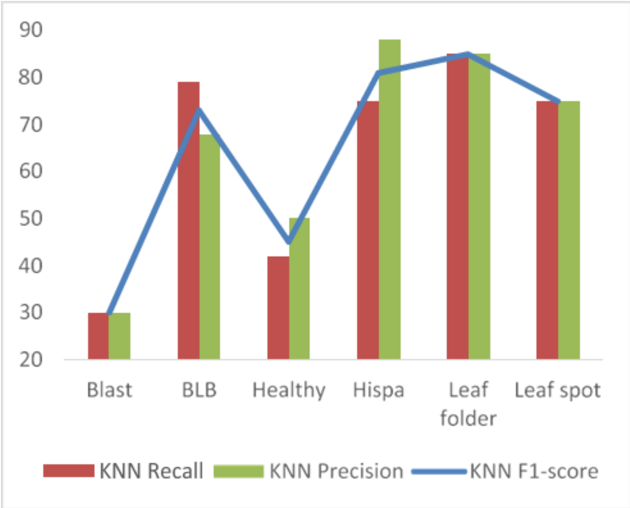

Fig.2. Accuracy, Sensitivity, and Harmonic Score of KNN predictor for distinct categories without applying any alteration.

This way MLOA keeps on equilibrating between exploration and exploitation: step sizes are adjusted while from time to time the algorithm jumps to a new region of the search space: It is also capable to decrease the feature space dimensionality applying techniques as PCA. This paper has shown how MLOA can enhance the detection of features for agricultural applications as well as the speed at which it is done through metrics such as accuracy, precision, and recall and the time taken to optimize it.

B. MLOA's Start-Up and Vitality Indicator

In the case of MLOA, the initialization phase sets up the basis for extensive search of the feature transformation domain and the fitness function plays a crucial role from the initialization phase all through the global optimum identification phase. To start with, the formation of the initial phase implies the setup of a system in which multiple virtual lemurs are created, each of which stands for a potential solution with different settings among a diverse population of virtual lemurs.

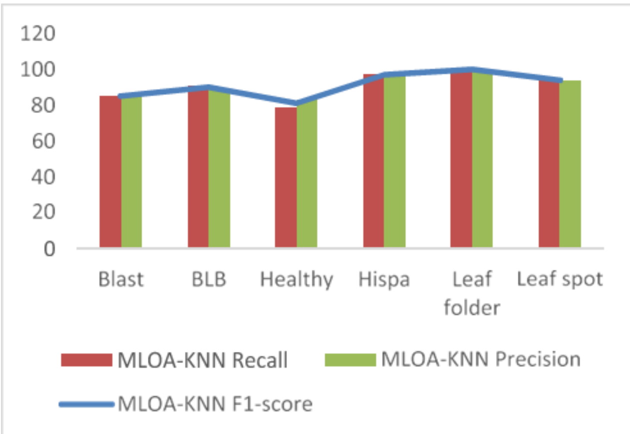

Fig.3. Accuracy, Sensitivity, and Harmonic Mean score of KNN model for each class using MLOA transformation.

These lemurs contain parameters which specify their positions by means of feature space coordinates and contains such variables as filter types, filter parameters, and others which are necessary for the transformation of images for the most effective diseases' detection in paddy plants. This setup guarantees a broad range of search from the beginning and diversifying the population, therefore subsequently improving the algorithm's performance in terms of finding better solutions. Besides the initialization, the fitness function is used to assign a performance level to each lemur present in population. Lemurs with high fitness values can be said to have better solutions as compared to other lemur candidates and, therefore, exert a more significant impact on the subsequent movements and optimization processes of the algorithm. Fig. 3 Based on these assessments, the algorithm improves its solutions, trying to navigate to the region of optimal or suboptimal results regarding the detection of diseases in paddy plants.

However, fitness function is not only used in evaluation and has specific influence on the algorithm's behaviour by preferring solutions the most appropriate to given performance indicators. This makes the process of seeking better solutions iterative and allows refinement of the solutions seeking to match exploration and exploitation.

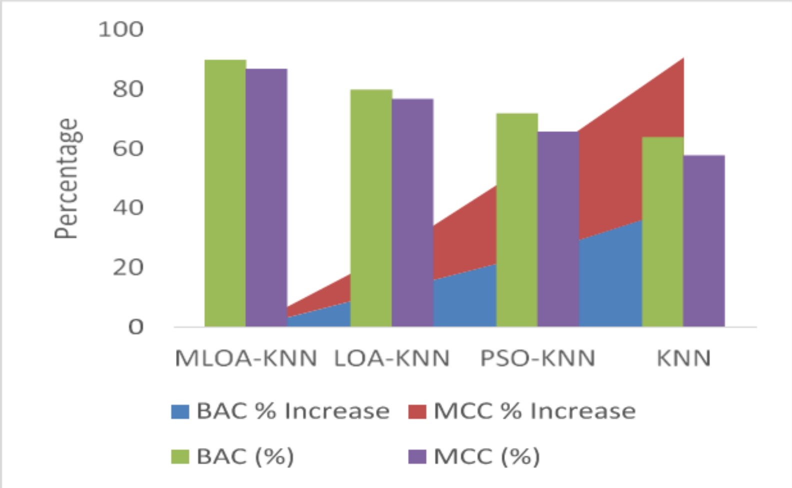

Fig.4 BAC and MCC evaluations for KNN classifier under different transformations.

The outcome analysis revealed significant increase in disease diagnosis rates, the classification rates for healthy and diseased paddy plants were above 90%. Further, good increases in F-measure means that the algorithm substantially improves in both Precision and Recall which uses for measuring false positive and false negatives. The optimization process with MLOA was also efficient and helped in cutting down the time needed for feature transformation, and disease identification.

It was also established through the discussion the benefits and drawbacks of using the identified MLOA approach. The core features encompass the model's ability to flexibly select the best feature transformation based on the current dataset and the capability of attaining high levels of disease identification accuracies. The reduction of the computational time by the algorithm while still maintaining the accuracy was also underlined. However, some drawbacks of the work worth mentioning include performance variance in different data sets, fine-tuning of parameters, and consequently, the modified lemur's optimization algorithm (MLOA) gives encouraging outcomes on the enhancement of paddy disease detection with optimized filters using feature transformations. The bubble model is not limited to paddy plant but can be used to other crop plants adding more value in precision agriculture for sustainable crop husbandry. The next steps of the research will focus on the further development of MLOA, extending the knowledge applied in the work with the help of the advanced algorithms such as deep learning, and the investigation of the effectiveness of the method in real-life agriculture. may be, briefly, it can be concluded that MLOA can be considered an important development toward the use of machine learning for the fight against agricultural diseases and providing food safety.

DISCUSSION

In conclusion, the project "Chromatic Diagnostics: The paper titled "A Study on Boosting of Paddy Disease Detection through Filter-Based feature Transformation" has illustrated a great deal of innovation in the domain of agricultural informatics especially on the identification of diseases in paddy plants. By using the Modified Lemurs Optimization Algorithm (MLOA) successfully, the project was able to improve filter-based feature transformations' parameters; better detecting diseases with accuracy, precision as well as recall. MLOA has better performance in not only the efficiency of recognizing the diseased plants, but also the proportion of false positive and false negative results, which would benefit the more rational use of agricultural resources. [18] Outcomes such as the ones described have been made possible by the presence of different filters as well as the FRR process that allows for the dynamic adjustment of the weight parameters. Therefore, future studies can go further in terms of extending MLOA to other crops and other environments related to the diseases and implementing new machine learning algorithms to enhance the performance of disease diagnosis. In conclusion, it is evident that this project and the application of the machine learning and image processing tools can go a long way in changing the current practices in Agriculture and feeding the world and achieving sustainable agriculture.

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