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Optimized Matrix Feature Analysis – Convolutional Neural Network (OMFA-CNN) Model for Potato Leaf Diseases Detection System

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Abstract— One of the most often grown crops is the potato. As a main food, potatoes are prioritised for cultivation worldwide. Because potatoes are such a rich source of vitamins and minerals, we can create a robust system for food security. However, a number of illnesses delay the growth of agriculture and harm potato output. Consequently, early disease identification can offer a better answer for effective crop production. In this research work aim is to classify and detect the potato leave (PL) diseases using OMFA-CNN deep learning model. An optimized matrix feature analysis-CNN deep learning model for PL disease detection is implemented. In the first phase, the PLs features are extracted from the potato leave images using K-means clustering image segmentation method. At the last phase, a new OMFA-CNN model are proposed using CNN to classify virus, and bacterial diseases of PLs, The PL disease dataset consists 2351 images gathered in real-time and from the Kaggle (PlantVillage) dataset. The implemented OMFA-CNN model attained 99.3 % precision and 99 % recall on potato disease detection. The implemented method is also compared with MASK RCNN,SVM and other models and attained significantly high precision and recall.

Keywords-PL (potato leaf) diseases;Segmentation; Feature Extraction; Deep Learning ; OMFA- CNN (Optimized matrix feature analysis convolutional neural network).

I. INTRODUCTION

There are several categories of professions throughout the world; however, farming is the most ubiquitous. The economic condition of India, which is heavily dependent on agriculture, is no exception. The potato plant is a highly adaptable crop, accounting for around 28.9 percent of the cultivated crop production in India. Consequently, potatoes are the world's 4th biggest farming food harvest, after alternative crops such as maize, wheat, and rice. India is the 2nd highest maker of potatoes in the world, with 48.5 million tons formed annually. According to a report by the Agricultural and Processed Food Products Export Development Authority (APEDA), Uttar Pradesh (UP) is the highest potato maker in India, accounting for around 30.33 percent of the total manufacture.

Current agricultural observations are extremely challenging issues. The agricultural sector has undergone enormous economic and global development, in which farmers and other performers have to consider not only native climatic and ecological features but also universal biological and administrative influences to confirm their financial survival and maintainable manufacture. Potato is an effective harvest and a great source of protein, dehydrated substances, and minerals per unit area compared to breakfast cereal. Though, potato manufacture is exposed to several illnesses, leading to crop losses, reduced storage organ quality, and increased potato costs. Numerous diseases, especially fungal infections, affect potato yields, resulting in significant crop revenue losses and major financial losses for farmers and producers.

Potatoes are an excessive source of potassium, vitamins, specially C and B6, and fiber. They reduce the overall saturated fatty acid levels in the blood and support disease diagnoses such as high blood pressure (BP), heart disease, and melanoma. Plant and farming properties are harmed by syndromes caused by bacteria, chromosomal illnesses, and infectious agents such as bacteria, mildew, and viruses. Potato foliage diseases are mainly caused by fungi and microorganisms. Potato agriculture is a profession in the cultivation area in around 125 nations. However, even these root crops are susceptible to impurities and diseases, especially early and late blight, as shown in Figure 1.

Due to these syndromes, the crops are damaged, and their production is reduced. Root vegetables have an additional favorable nutrient-to-price ratio compared to other fruits and vegetables and are a reasonable source of global food. Late and early blight are mycological diseases, while soft rot and common scabs are bacterial. Detecting and diagnosing illnesses on dynamic plants inspires us to formulate an automatic policy or method to improve crop yield, increase agriculturalist income, and significantly contribute to the nation's budget. Traditional approaches and visual reviews are generally used to identify and analyze plant illnesses. However, these techniques have some difficulties, as they are costly due to repeated observations by specialists and are time-consuming. Moreover, specialists are not always available in the vicinity [6].

Figure 1. Potato Leaf Diseases [5]

Late blight harms potato leaves, branches, and roots, appearing bubbled and dried. When drying out, the leaves turn brown or black. The solution to this issue is great moisture, cold, and leaf humidity. The major blight may appear on the potato leaves at any expansion phase, affecting distinguishing foliage spots and blight. It can be detected as a small black scratch on the older leaves. Several lesions on the potato plant's branches, as well as those on the leaves, are moderately visible, occasionally girdling the vegetable if they occur near the top layer of the soil line. The solution to this challenge is a warm, damp, rainy, and showery climate [7].

Identifying leaf diseases in potato plants is a crucial process to reduce the impact of infections on plants. However, manual or labor-intensive monitoring actions assigned by agriculturalists become difficult and impractical due to their time-consuming processes and detailed knowledge requirements. Failing to identify slow potato plant infection forms will lead to the rapid spread of syndromes in plants. Moreover, agriculturalists typically recognize illnesses in potato plant leaves in a specific way that is subjective and relies on expectations, resulting in poor detection outcomes. This is because the symptoms of the illnesses that appear on the leaves have correspondences that are challenging to clarify at a glance. Agriculturalists require selective detection outcomes without professional guidance in potato plant illnesses to prevent plant infection. Consequently, protective methods utilized by agriculturalists might be unsuccessful and harm yields, leading to insufficient facts and misunderstandings of infection strength, excessive quantity, or lack of dose [8][9].

The existing work [13] was developed for the disease detection and the classification which occurs for the potato plants. For the existing work, the open access, standard, valuable database was measured that was famous called as Plant Village database. For the procedure of potatoes leave image segmentation K-means clustering method was measured, for the feature extraction motive grey-level co-occurrence matrix (GLCM) concept was used, for the classification purpose MSVM classification was used. The research methodology able to achieve an accuracy of 95.9 percent. **Monzurul Islam et al. 2017 [11]** discussed the automated detection method on potato plants from online dataset available known as “Plant Village”. The author introduced segmentation method and used for SVM classification method over 300 images with an accuracy value of 95 percent.

The current research implemented DL model for potato leaf disease detection (PLDD). In the initial phase, PLs are preprocessed and noises are removed followed by image segmentation. The reliable features are then extracted using PCA and GLCM methods. It extracts the texture-based features at the 2^{nd} phase. After the feature extraction firefly method is applied to select the valuable feature vector to move forward to the model defined in the third phase. An optimized matrix feature analysis-convolutional neural network (OMFA-CNN) has been introduced at the phase forth to detect the early-stage potato diseases from potato leave images. So, the presentation of the implemented OMFA-CNN model calculated in the potato leaf database.

The following are the contribution of this proposed work:

- A real-time optimized matrix feature analysis-convolutional neural network method has been proposed using Kaggle (Plant Village) potato leaves (PLs) .
- A new DL method known as optimized matrix feature analysis-convolutional neural network (OMFA-CNN) has been developed to detect early-stage diseases from potato leaf images.
- A potato leaf disease database has been created by collecting various categories of potato leaf images from Kaggle (Plant Village).

The rest of the paper is managed as related work is represented in sect. 2, proposed methodology is in sect. 3, and result discussion are defined in sect. 4, while sect 5 defines the conclusion followed by the references.

II. RELATED WORK

This section describes several existing kinds of research regarding potato leaf disease detection. Several plant diseases have reduced the performance of farming growth rate and economic view of any country. So, need is required to detect these infections at an earlier stage and use remedies timely. Several methods and existing methodologies used in this field

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is analyzed and explained here. In **2021, Joe Johnson [10]** developed an automated scheme through the mask region-based convolutional neural network (CNN) construction to overcome these problems. This system was developed through the residual approach and was considered the backbone for sensing blight illness reinforcements on potato leaves in field situations. The proposed method required transfer learning (TL), which can generate good outcomes even using small datasets. The proposed model was accomplished on 1423 imageries of potato leave datasets from pitches in several geographic situations. The mask region-based CNN model appropriately distinguished between the unhealthy reinforcement on the potato foliage and the similar-looking contextual territory patches, which can confuse the conclusion of twofold classification. The innovative RGB dataset was used to advance the recognition performance and then transformed into a different format, such as HSL, HSV, LAB, XYZ, and YCrCb color spaces. The proposed model achieved a mean average precision of 81.4% using the LAB model and a mean average recall of 56.9% using the HSL model. In **2019 Monzurul Islm et al. [11]** developed a methodology that combined image processing (IP) and ML to permit analyzing of sicknesses from foliage imager. This computerized proposed method organizes infections on potato plant life from an openly accessible plant appearance databank termed 'Plant Village. So, the proposed segmentation method and application of support vector machine (SVM) validated illness classification completed on 300 imageries and achieved an accuracy of 95%. Therefore, the suggested method presents a path toward automatic plant illnesses analysis on an enormous measure. In **2020 [12] Divyansh Tiwari** described the improvement in farming expertise and the practice of artificial intelligence (AI) in identifying plant illnesses. It was developed as significant to create related investigation to supportable agricultural growth. Numerous infections comparable to early blight and late blight enormously impact the superiority and measure of the vegetables, and physical interpretation of these leaf diseases was moderately time-taking and unmanageable. This process required an extremely decent level of proficiency, effective and automatic recognition of these illnesses in the growing stage, and assistance in upgrading the potato yield construction. Earlier, numerous prototypes have been recommended to distinguish numerous plant infections. The authors proposed a model that was reachable through the observation of pre-trained models such as VGG19 intended for transfer learning (TL) to abstract the appropriate structures preliminary the dataset. At that time, with the support of several classifiers, outcomes were observed, amongst which logistic regression (LR) outperformed additional through a substantial border of classification performance of accuracy attained 97.8% above the experiment dataset. **Aditi Singh et al., (2021) [13]** described farming as one of the important regions for the persistence of humanity. At a similar time, digitalization was interrelated with all the fields that became informal to switch challenging responsibilities. Adapting skills and digitalization were identically essential and designed for farming to assist the agriculturalist and the consumer. Adopting techniques and consistent observation allowed one to identify the sicknesses in the preliminary phases, and those can be eliminated to attain improved harvest revenue. The authors proposed a method to recognize and categorize illnesses in potato plants, and a reliable dataset was utilized, commonly recognized as Plant Village Dataset. The K-means method was used for the image segmentation procedure, and the gray level co-occurrence matrix (GLCM) perception was utilized for the feature extraction process. The multi-class SVM practice was employed, and the proposed method attained an accuracy of 95.99%. **Anushka Bangal et al. (2020) [14]** develop an automatic and rapid infection detection procedure for the growth of potato production and digitize the scheme. The main motive of the authors was to develop an automatic and rapid infection detection procedure for the growth of potato production and digitize the scheme. The proposed method was utilized to diagnose potato illness by foliage representations using the CNN method. The proposed method offered a treatment concept, and machine learning-based automatic systems of potato leaf illnesses were identified and classified. For this motive, 2000 images of strong and harmful vegetable leaves from Kaggle and insufficient pre-arranged models were employed to respond to and classify strong and unhealthy plants. The developed technique attained an accuracy value of 91.41% with the database. **Javed Rashid et al. (2021) [15]** proposed an unconventional multi-level DL model designed for PL illness appreciation. The proposed model based on PL illness recognition was accomplished and verified on a PLDD. The potato leaf disease dataset contains 4062 images from the Central Punjab area of Pakistan. So, the introduced model reached an accuracy of 99.75% using the PLDD. The presentation of the suggested methods was calculated on the Plant Village dataset, compared through the modern models, and attained considerably regarding the accuracy and measurable cost. **Yanlei Xu et al., (2022) [16]** described several disease concerns for agriculture and initiated economic damage for cultivators. Thus, disease identification was addressed primarily for accuracy in agriculture. The DL method was compulsory for illness identification gathering and collecting optical imaging sensors. The authors established a lightweight CNN model with openly accessible plant imaging datasets. The proposed model extended accuracy of 99.86% through 0.173 seconds speed. **Natnael Tilahun Sinshaw et al., (2022) [17]** designated the commercial view of developing states based on farming. The influence of agriculture on naive home development was a major issue. Plant disorder was the main

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reason that severely affected yield manufacture. The authors projected a depiction of various potato syndromes. The computerized techniques were hired for potato disease detection, and different ML techniques required were described. **Rizqi Amaliatus Sholihati et al., (2020) [18]** defined the potato plant as an important and most utilized fourth food in worldwide. Also, the global demand for potatoes was growing expressively due to the coronavirus. But the potato impurities were the main reason for crops' quality and growth degradation. The specialists projected a model to consolidate the four potato diseases based on diseased leaves. For this motive, DL and two CNN models such as VGG-16 and VGG-19 were utilized and reached 91% of accuracy, identifying the prospect of the DNN technique. **Yue Shi et al., (2022) [19]** defined a perfect and automatic investigation of potato diseases such as late-bight illness was measured as an exceptionally harmful infection. This type of disease was critical for precision sophisticated control and tool. The authors projected a perfect Crop_doc_Net model to detect potato disease efficiently and automatically. The UAV-based hyperspectral dataset was used for this proposed. The authors deliver the best performance of the proposed structure with the dataset mentioned above. The projected model attained a 98.09% of accuracy for testing and 95.75% for independent datasets. **Hassan Afzaal et al., (2021) [20]** offered the vision of automation of DL models to identify diseases earlier for potato model manufacturing. The authors proposed a model using a specific dataset that was constructed using the DL method to distinguish the various phases of disease at an earlier stage. The projected model attained F1-Score by comparing Google_Net, VGG_Net, and Efficient_Net. **Md. Asif Iqbal et al., (2020) [21]** defined potato plants as utilized nutrition crops worldwide. Potato agricultural extended major authorization in Bangladesh completed the earlier years. Some disorders disturb potato food production, and diseases were recognized in the potato. The authors projected an image processing and ML-based automation model to distinguish and organize potato leaf disorders. The image segmentation process performed with 450 potato leaf images was used in two forms, infected and non-infected, retrieved from PV datasets. The proposed model extended an accuracy of 97% using an RF classifier. **Jennifer Eunice et al., (2022) [22]** defined the cultivated field as essential in food quality involvement and advanced the utmost influence to recover thrifts and the general public. The journalists projected CNN-based pre-proficient models for real plant disorder recognition. The journalists were suggestively sophisticated in the hyper-parameters of existing Restnet-50, VGG-16, DenseNet-121, and inception-V4 pre-proficient models. The authors carried out the outcomes of the projected model through the PV dataset, reaching 99.81% of accuracy. **Jaemyung Shin et al., (2022) [23]** improved automatic automation using the cultivational field as significant to the food demand of quickly cumulative individuals. Similarly, wide-ranging labor and intervals were employed in agriculture. So, agriculture computerization was a serious and early matter. Computer-vision-based mechanization could improve effectiveness and value over error decline and combined portability to the determination process. The proposed consideration offered a framework of computer-vision practices for burden or disorder recognition on harvests, leaves, fruits, and potatoes using novel analysis techniques established and future direction in correctness agriculture. **Minah jung et al., (2022) [24]** described disease precision existences of crops in the prior stage as significant for the dominance and crop yields to excellent of appropriate analysis. Then, the revelation to plant disease needed committed realities and extensive practice in plant pathology. The authors projected the CNN, a step-by-step disease detection model, by arranging healthy and infected plant leaves. The launched model extended an accuracy of 97.09% in crop classification and disease types and broadly organized the projected model on perfect, innovative cultivation. **Ali Arshaghi et al., (2022) [25]** defined the practice of processing and automatic methods as significant in evaluating crops' lack, mainly root potatoes. The authors projected the model with CNN models and experiential five classes of potato illnesses types as in decent physical shapes of five thousand potato imageries. The projected model extended an accuracy of 99%. **Khursheed Aurangzeb et al., (2020) [26]** labeled various diseases with lousy impact on the financial view for a state-run. That was the most critical factor for these challenges' elimination. Thus, the authors built a computerized model for identifying corn and potato diseases. The authors used histogram-oriented gradient (HOG), local ternary patterns (LTP), and fragmented fractal surface investigation methods for feature extraction. Then, the PCA technique was employed alongside entropy. Skewness in score weights was estimated for the proposed model and the problem reduction. The PV dataset was used to provision and classify certain plant infections and retrieved with 98.70% accuracy. **Theyazn H. H. Aldhyani et al., (2022) [27]** defined the agriculture field as a strength of the worldwide economy. This zone faced the critical largest problems in crop disease recognization, prediction, pest regulation, early detection, and yield prediction, distinguishing between superiority and food making. The authors projected an inventive CNN model for yield disease classification and utilized a PV dataset with 38 forms and 15 classes. The projected model's results attained better performance at 91.28% of accuracy. **Macro Javier Surarez Baron et al., (2022) [28]** proposed research was accepted in the Boyaca branch in Colombia and the primary dataset was designed through many crop images. These images were applied to basic feature extraction of late blight disease. The classification technique was made to differentiate the detection process of infected and

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non-infected potato leaves. The projected method correspondingly extended AUC values of 0.97 and 0.87 for the CNN and SVM. **Yu Oishi et al., (2021) [29]** defined potatoes as a universally consumed plant. The diseased potato leaf was neighboring ten root potato storing structures, and the disease can vary to the depths potato developed rotation. The building of potato analysis to grow the outstanding bud potatoes that were healthy and non-infected delivered. The authors projected a computerized asymmetrical potato leaf detection model that inspired a handly audio-visual capturing method and DL models to care for detailed identification. The projected potato leaf detection model extended by 90% and 78.20% of accuracy and regular precision, respectively. **Monika Lamba et al., (2021) [30]** defined an analysis of potato plant disorders as a severe portion of better knowledge of a nation's economic perspective in the form of undeveloped harvest. The preliminary detection and procedure of conditions in root plant leaves were vital as they can seriously fault the class manufacture and development. The authors projected a model that contained an auto-color correlogram as an image filtering, and the DL utilized various activation functions (AFs) for plant leaf viruses. The projected model utilized four datasets and extended 99.4% accuracy and 99.9% precision for binary class and multi-class.**Md. Ashiqur Rahaman Nishad et al., (2022) [31]** described potato as one of the widely sophisticated yields. The potatoes were their farming significance as leading nutrition. The authors proposed a robust nutrition safety model for better production of the potato plant, and it was an excellent source of vitamins and carbohydrates. Various infections degrade the potato plant's production and the country's economic growth. Detecting disease at the initial phase provided significant results for better crop farming. The authors utilized the K-means cluster segmentation method to improve the efficiency of the model and several data augmentation methods were used to train data. The proposed model obtained 97% accuracy, with VGG-16 considered best compared to other VGG-19 and RestNet-50 models. **Akey Sungeetha (2022) [32]** defined self-governing learning and feature extraction benefits as recognized attention in previous years. The authors projected analysis about leaf infection recognition and diagnosis established throughout image segmentation employed in the composition of DL or ML models. The authors measured the performance parameters of the previous research, which delivered further direction in plant leaf disorders analysis and identification methods.

Neeraj Rohilla et al., (2022) [33] described the essential role of the agricultural manufacturing field in India's commercial growth. This field accounted for around 70% of economic growth. Land degradation was the main reason for the loss of production, which badly disturbed the economy. Plant leaves disease initially visible on leaves played an essential role in predicting any plant leaf disease. The supplies must be observed for illnesses from their lifespan until the preparation garnering. The authors represented pre-processing unit for processing the image in the early phase and provided transparent objects and standardized image content. Another described feature extraction process was completed with GLCM and HOG methods.The segmentation process was finished using Kmeans clustering and reached the least error rate during training and testing any image sample using classifiers. **Neeraj Rohilla et al., (2022) [34]** described farming manufacturing as an essential domain for economic growth in India. Nearby 70% part of economic growth was based on the farming domain, and land degradation reduced production. The authors initially developed a pre-processing unit for processing the image in the early phase and provided transparent objects and consistent image content. Another described feature extraction (FE) procedure was completed with GLCM and HOG methods. The segmentation procedure was done using K-means clustering and reached a nominal error rate during training and testing any image sample with classifiers.

Table 1 discussed the different methods and existing methodologies, datasets, performance metrics, simulation tools here. Analysis the several articles with different methods or models, datasets, different parameters such as accuracy, precision, etc., After that identified the existing outcomes.

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TABLE I. ANALYSIS OF THE POTATOE DISEASE DETECTION SYSTEM

Sr. No.	Title with Year	Authors	Models	Datasets	Metrics	Findings/Outcomes
1.	Enhanced field-based detection of potato blight in complex backgrounds using deep learning (2021).	Joe Johnson	Mask RCNN LAB HSL HSV XYZ YCrCb models	MS COCO Dataset	Tp, Fn , Fo, P, R	81.4 % mean average P on the LAB and 56.9 % mean R on the HSL models.
2.	Detection of potato diseases using image segmentation and multiclass support vector machine (2020).	Monzurul Islm et al.	SVM GLCM	PlantVillage	Accuracy	Disease classification over 300 Images with accuracy value of 95%
3.	Potato leaf diseases detection using deep learning (2020).	Divyansh Tiwari	Inception V3 Vgg-16 Vgg-19 FT LR	Kaggle (Plant Village)	Accuracy	Classification accuracy rate attaining 97.8 % over the test database.
4.	Potato plant leaves disease detection and classification using machine learning methodologies (2021).	Aditi Singh et al.	k-means MSVM	Plant Village	Precision Recall F1-score Accuracy	Proposed model able to attain an accuracy rate of 95.9 %.
5.	Potato Leaf Disease Detection And Classification Using Cnn (2020)	Anushka Bangal et al.	CNN	Kaggle (Plant Village)	Accuracy	CNN model detection of disease accuracy value of 91.4%.
6.	Multi-level deep learning model for potato leaf disease recognition (2021)	Javed Rashid et al.	MLDL model PDDCNN	Plant Village	Accuracy Precision Recall F1-Score	The plant disease dataset has achieved accuracy value of 99%.
7.	HLNet Model and Application in Crop Leaf Diseases Identification (2022).	Yanlei Xu et al.,	CNN model	PV dataset	Accuracy	This model reached 99.86% of accuracy.
8.	Applications of Computer Vision on Automatic Potato Plant Disease Detection: A Systematic Literature Review (2022).	Natnael Tilahun Sinshaw et al.,	SVM GLCM	PlantVillage (PV)	Accuracy	This model reached overall 99% of accuracy.
9.	Potato leaf disease classification using deep learning approach (2020).	Rizqi Amaliatus Sholihati et al.,	VGG-16 VGG-19	Potato leaf dataset	Accuracy	This model reached 91% of accuracy.
10.	Novel CropdocNet Model for Automated Potato Late Blight Disease Detection from Unmanned Aerial	Yue Shi et al.,	----	UAV-based hyperspectral dataset	Accuracy	This model reached 98.09% of accuracy.

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	Vehicle-Based Hyperspectral Imagery (2022).					
11.	Detection of a potato disease (early blight) using artificial intelligence (2021).	Hassan Afzaal et al.,	Google_Net, VGG_Net, Efficient_Net.	532 image datasets.	Accuracy Precision Recall Training-Loss Fi-score	This model reached 99% of accuracy.
12.	Detection of potato disease using image segmentation and machine learning (2020).	Md. Asif Iqbal et al.,	RF LR KNN DT NB LDA	PV datasets.	Accuracy Precision Recall F1- score	This model reached 97% of accuracy.
	Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications (2022).	Jennifer Eunice et al.,	Restnet-50, VGG-16, DenseNet-121, and inception-V4	PV dataset	Accuracy	This model reached 99.81% of accuracy.
13.	Trends and Prospect of Machine Vision Technology for Stresses and Diseases Detection in Precision Agriculture (2022).	Jaemyung Shin et al.,	-------	Massive dataset	----	-----
14.	Construction of Deep Learning-Based Disease Detection Model in Plants (2022).	Minah jung et al.,	DL based model	plant pathology	Accuracy	This model reached 97.09% of accuracy.
15.	Potato diseases detection and classification using deep learning methods (2022).	Ali Arshaghi et al.,	CNN model	PV dataset	Accuracy Precision Recall	This model reached 99% of accuracy.
16.	Advanced machine learning algorithm based system for crops leaf diseases recognition (2020).	Khursheed Aurangzeb et al.,	PCA model	PV dataset	Accuracy	This model reached 98.70% of accuracy.
17.	Leaf Pathology Detection in Potato and Pepper Bell Plant using Convolutional Neural Networks (2022).	Theyazn H. H. Aldhyani et al.,	CNN model	PV dataset	Accuracy	projected model's results attained better performance at 91.28% of accuracy.
18.	Supervised Learning-Based Image Classification for the Detection of Late Blight in Potato Crops (2022).	Macro Javier Surarez Baron et al.,	CNN SVM	Image dataset	AUC	The proposed model reached AUC values of 0.97 and 0.99 for both classifiers.

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19.	Automated abnormal potato plant detection system using deep learning models and portable video cameras (2021).	Yu Oishi et al.,	YOLO R-CNN	PV dataset	Accuracy Precision recall	The proposed model reached 90% and 78.20% of accuracy and regular precision, respectively.
20.	Classification of plant diseases using machine and deep learning (2021).	Monika Lamba et al.,	KNN NB LIbSVM DT	Tomato Rice Pepper bell Potato dataset images	Accuracy	The proposed model reached 99.4% accuracy and 99.9% precision for binary class and multi-class.
21.	Predicting and Classifying Potato Leaf Disease using K-means Segmentation Techniques and Deep Learning Networks (2022).	Md. Ashiqur Rahaman Nishad et al.,	VGG-19 and RestNet-50 models	PV dataset	Accuracy	Proposed model obtained 97% accuracy.
22.	State of Art Survey on Plant Leaf Disease Detection (2022).	Akey Sungeetha	AlexNet, GoogLeNet, ResNet SVM	Different types of plant leaves images	Accuracy	Proposed model obtained 98.4% accuracy.
23.	Advance Machine Learning Techniques Used for Detecting and Classification of Disease in Plants: A Review(2022).	Neeraj Rohilla et al.,	GLCM HOG K-means SVM NB DT	Different types of plant leaves images	--	--
24.	Automatic Image Segmentation and Feature Extraction of Potato Leaf Disease Using GLCM and HoG Features (2022).	Neeraj Rohilla et al.,	GLCM HOG K-means HSV RGB	PV dataset	Accuracy Smoothness RMSE SD Entropy Mean	Model achieved better accuracy as compared to existing.

Acronyms: R-CNN (Mask Region-Based Convolutional Neural Network), Tp(True Positive), Tn(True Negative), Fn (False Negative), Fp(False Positive), P (Precision), R(Recall), LR(Logistic Regression),FT(Fine-Tuning),MSVM(Multi-class Support Vector Machine), CNN (Convolutional Neural Network), MLDL (Multi Level Deep Learning Model), PDDCNN(Potato Leaf Disease Detection using Convolutional Neural Network)

III. Research Methodology

Several issues occur in the related work using DL methods, including inaccurate detection of potato leaf diseases, difference in potato diseases (PDs). The previous developed systems have a maximum false rate (FR) to detect PDs. The available datasets for Potato Leaf Disease (PLD) have limited training samples and suffer from imbalanced class distributions. Moreover, existing techniques exhibit slow training speeds due to a large number of training metrics, which hinders their accuracy improvement. The OMFA-CNN model is implemented to classify the disease in this research work. At the initial phase, it extracts the potato leaves from the plant image using Plant Village image segmentation, and extracts the reliable feature using principal component analysis (PCA), and GLCM methods. It extracts the texture-based features at the second phase. After the feature extraction firefly method is used to select the valuable feature vector to move forward to the model defined in this third phase. An optimized matrix feature

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analysis-convolutional neural network (OMFA-CNN) has been introduced at the phase forth to identify the early stage diseases from potato leave images. The flow diagram of the research approach is defined in Figure 2, the OMFA-CNN algorithm 1 is discussed, and the research work overall design is defined in Figure 3.

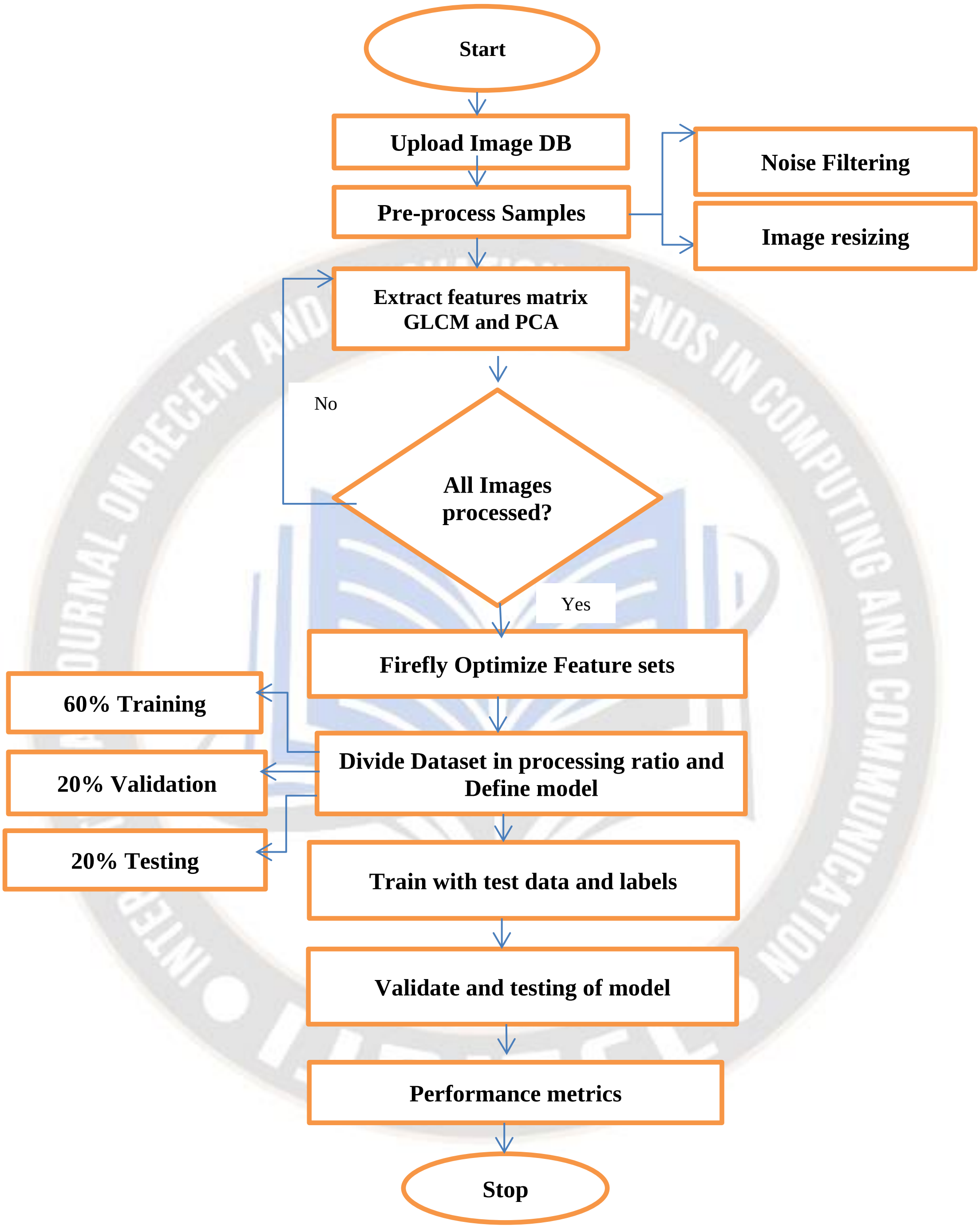

Figure 2. Flow Chart of Proposed Model

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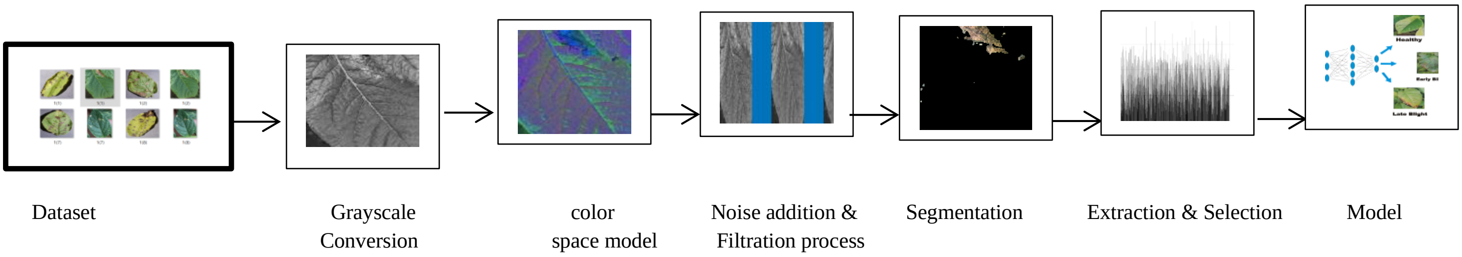

Figure 3. Complete Design of the research model

Algorithm 1: Optimized matrix feature analysis-convolutional neural network (OMFA-CNN)

Input Data:
- Train_db Image
- Test_db Image
- Population size (selected_features)
- No. of iterations

Output:
- Detected disease categories
- Classification
- Evaluate the performance metrics.

Step 1: Input Image
[a,b] = uigetfile('*.jpg','select an image from the dataset');
Comp = strcat(b,a);
Input_img = imread(Comp);
Figure,
Imshow(Input_img);
Title('Input Image');
Step 2: Resize the uploaded image [0-255]
Dimg = imresize(Input_img, [256,256]);
Step 3: Convert the color RGB image into Grayscale Image
Gimg = grayscale (Dimg);
Step 4: Add artificial noise
Nimg = imnoise(Gimg,'Salt & Pepper',0.2);
Step 5: Applied the filtration method (i) 3D box filter and (ii) Gaussian filter.
Fimg = 3D (Nimg);
Step 6: Applied Color space model (HSV).
Step 7: Developed K-means clustering method used for segmentation process.
Suppose x = {X1,X2, X3,…….,Xn} be the set of data-point and c ={C1,C2,…….,Cn} be the set of centers.
Random selection "K" cluster center.
Evaluate the distance d between each data-point and cluster center.
Assign the data-point to the cluster center whose distance from the center of cluster is less than all the cluster centers,
Reevaluate the novel cluster center.
Reevaluate the distance between each data-point and novel attained center clusters.
If no data (img) was reassigned then stop, otherwise cluster data.
Step 8: It introduced the feature extraction method i.e., PCA, GLCM, etc.
Potato leaf Image.
Vector of texture feature sets.
Initialize
Computing GLCM matrix for different directions with distance d=1.
Algorithm call of normalizing each GLCM matrix.
For each GLCM matrix in particular angle.
Evaluate texture feature sets acc. To their eq.
Saved evaluated feature sets in a vector.
End
GLCM metrics: It extracts the texture-based feature set.
Features are; Energy, correlation, homogeneity, entropy, mean, etc.
PCA (Eigen values, Eigen vectors).
Standardize the potato leaf image dataset
Explore the eigenvalues (E), and Vectors (V)
Arrange E
Transform real image dataset
Rebuilding image dataset

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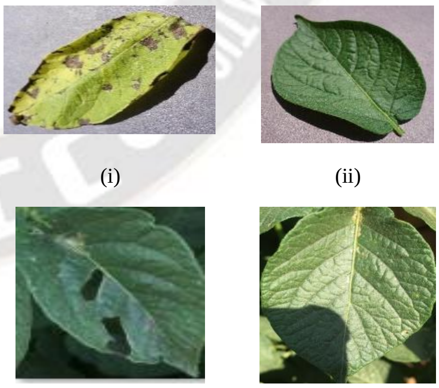
```
Step 9: It implements feature selection method using Firefly optimizer.
Step 10: It proposed OMFA-CNN model.
        Train the OMFA-CNN model with help of trained potato leaf images.
        Validate the OMFA-CNN model using a set of potato images at the end of each epoch for validation (20%) purposes.
        Save the train OMFA-CNN model.
        Test phase is applied to the OMFA-CNN trained model using test potato leaf images.
        Objective function (OF) F(y),y = (y1,…..yd)^t
        Generate initial_pop of fireflies yi = (I = 1,2,……,n).
        Light intensity Ii at yi is determined by F(yi)
        Define light absorption co-efficient z
        While (T<max_gene)
          For i=1:n all n fireflies
            For j = 1:n all n fireflies
              If (Ii<Ij) move firefly I towards j
        End if
        Vary attractiveness with distance r via exp. (z)
        End for j
        End for i
        Rank the fireflies and search the current global best G*
        End while
        Selected feature dataset
        For (i=0, i<l, i++)
         For (M =0, M<m, M++)
        {
        For (N=0, N<n, N++)
        {
        Sum = bias[1];
        For (K=0,K<k,K++)
        {
        For (S1=0, S1<s1,S1++)
        {
        For (S2 = 0, S2<s2, S2++)
        {
        Sum + = wt[K][L][S1][S2]*input[K][M+S1][N+S2];
        }}}
        Output[L][M][N] = activationFunction (sum);
        }}}
Step 11: Evaluate the performance metrics such as precision, recall, accuracy, etc.
```

A. Data Set and System Description

Potato leave images datasets was collected from (i) Plant Village dataset (https://www.kaggle.com/emmarex/plantdisease). Different categories of potato leave dataset images such as; Healthy, Virus, Insect, Alternaria solani, etc. Table 2 shows the different categories of potato leave images. Potato leaf image categories are shown in figure 4.

TABLE II. SUMMARY OF THE KAGGLE DATASET

Class Labels	**No. of Images**
Alternaria Solani	1055
Healthy	893
Insect Bite	302
Virus	1,012
Total Images	**2351**



(i) (ii) (iii) (iv)

Figure 4. Dataset Samples (i) Alternaria Saloni (ii) Healthy (iii) Insect bite, and Virus

The main steps of the potato leave diseases from the plant leaves are segmentation, feature extraction (FE), selection, and Classification. Individual of these steps will be defined in the later segments.

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B. Potato Leaf image Pre-processing

It was used on the potato leave diseases final images to improve classification outcomes consistency and enhanced feature extraction. The huge image dataset was required for the CNN method extensive iterative training in order to reduce the risk of over fitting.

- *Segmentation*

This section that will be segmented is mentioned to as the region of interest (ROI). Achieving it is very vital for the potato leaves to grab the designs available for each of the diseases. It was proposed by using [36] K-means clustering method. The method was introduced through the different phases such as;

- Regulate the no. of clusters.
- The centroid of each cluster will be randomly originated, and the no. of centroids measured is equal to the no. of clusters determined.
- Distance parameters will be developed to each cluster among each of the points and the centroid of that cluster.
    - Once a cluster of distances has been established, take into account the mean of those distances.
    - The mean value and update the centroid.
- Repeat the previous process until there is little to no change in the centroid of each cluster.

Several approaches are utilized for distance parameter like Euclidean distance (ED) as mentioned in eq (i). Figure 5 represents the segmented images of the potato leaf.

$$dist\,(x, y) = \left(\sum \left|X_j - Y_j\right|^2\right)^{1/2} \quad \ldots\ldots\ldots\ldots\ldots \text{(i)}$$

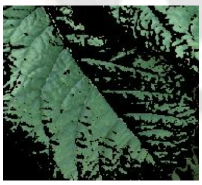

Figure 5. Segmented Potato Leaf Image

B. Feature Extraction

After the segmentation process was completed and attained the ROI. From this ROI, [35] the feature will be attained. The feature vector for the whole dataset will be very large. Thus, the significant features require to be extracted for the situation of classification. It can also be measured as a dimensionality reduction procedure as it fetches the vital data from a whole feature set such that no data remove out. The features extracted using the concept of combination of the PCA and GLCM matrices using several parameters. PCA extracts the features in the form of Eigen Values (E) and Eigen Vectors (V). GLCM parameters are shown in table III.

TABLE III. SUMMARY OF FEATURE VALUES AND NAMES

Feature Names	**Values**
Contrast	1.0181
Correlation	0.8152
Energy	0.2735
Homogeneity	0.891
Mean	53.82
SD (standard deviation)	57.58
Entropy	4.449
RMS	11.19

Figure 6 shows the extracted feature bar graph representation. PCA feature extraction processes are defined as below:

- Upload the ROI region data \\ Image to numeric data
- Normalize the upload data values
- Evaluate the covariance matrix
- Evaluate V of the covariance matrix \\ V (Eigen Vectors)
- Transform data using V.
- Invert PCA and rebuild read image data shown in figure 7.

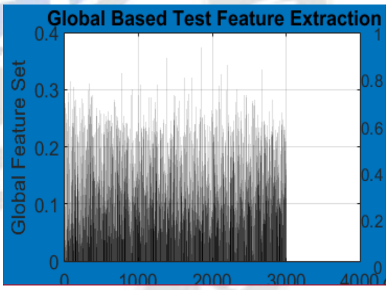

Figure 6. Feature Extracted Graph

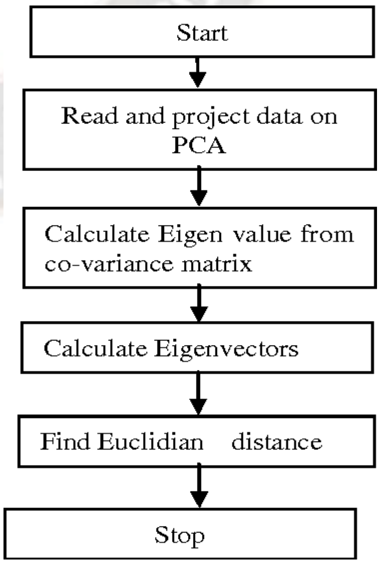

Figure 7. Feature Extraction Flowchartm

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C. Feature Selection

It plays a major role in enhancing the effective and precise potato leaf disease detection, a new method known as FFO (firefly optimizer) is used for feature selection. This method is an optimization approach inspired by the flashing nature of fireflies in environment. It aims to search the optimal subset of features which are most relevant to the detection of PLDs. By employing search through the high-dimensional feature space and to choose the most discriminative and informative features shown in figure 8. This procedure helps to optimize the dimensionality of the input data and eliminate redundant feature sets, leading to enhanced computational effectively and improved detection performance. The chosen features can then be utilized as input for classification method, such as CNN, to accurately classify and identify different types of Potato leaf diseases. Overall the integration of feature selection using FFO in PLD detection system gives a valuable tool for analyzers and experts in attaining more efficient disease diagnosis.

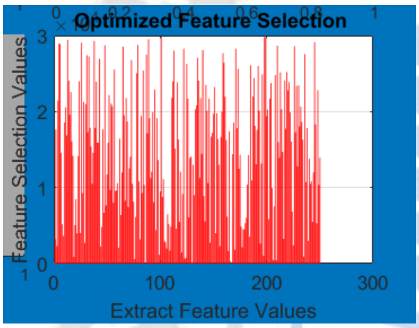

Figure 8. Selected Feature Sets

D. Optimized Matrix Feature Analysis-Convolutional Neural Network (OMFA-CNN) Model

The optimized matrix feature analysis-convolutional neural network model is introduced in this work for choosing and using the optimal feature sets. The input data defined in the method is shown in figure 9. The optimal feature selection makes the system more accurate and faster. The selection of the optimal feature sets measures the objective function defined in eq (ii), where accuracy defined the classified accuracy.

$$OF = \max(accuracy) \text{ .... (ii)}$$

$$\text{where accuracy} = \frac{Tp+Tn}{Tp+Tn+Fn+Fp}$$

Here Tp = true positive,Tn =True negative, Fp= false positive, Fn = False negative.

In this research work, an optimized matrix feature analysis-convolutional neural network is utilized for the classification procedure, where the number of convolution layers (CLs) is optimized. The initial representation is defined in figure 9(i). Here, CNn defines the total amount of CLs. Figure 9(ii) defines the decoding process of the solution encoding.

The proposed model importance developed CL mitigates the maximum dimensionality of images without losing its leaf dataset. Optimized matrix feature analysis-convolutional neural network model is very efficient in optimizing the no. of metrics without losing on the quality of models. All the layers of a CNN model have several convolutional filters working and scanning the whole feature matrix and fit network for image processing and classifications.

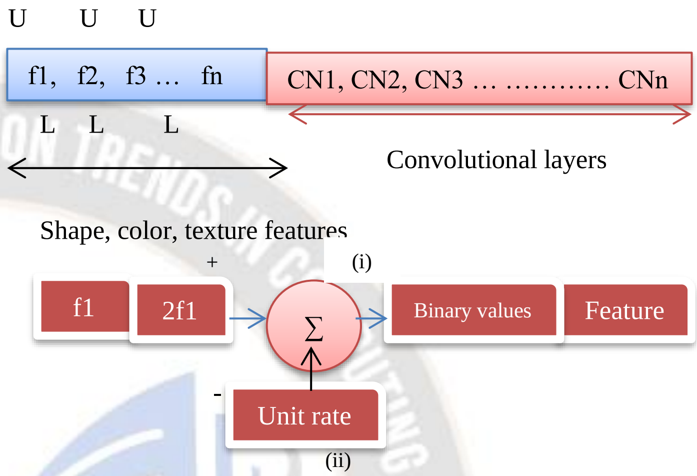

Figure 9 Encoding Solution (i) Representation (ii) Decoding process for the solution

Figure 10 based on the extracted feature, the images require to be divided into different classes such as healthy, insect bite, virus, etc. For the classification motive the OMFA-CNN model is used. It is supervised learning (SL) approach where detection of potato leaf image by trained dataset. CNN method helps neural network (NN) to detect or identify the potato leaves depends on the attributes. NN utilizes pixels in the potato leaf images to recognize the diseases.

The proposed work used the OMFA-CNN model in detecting diseases in potato leave images using different CLs and max pooling layers.

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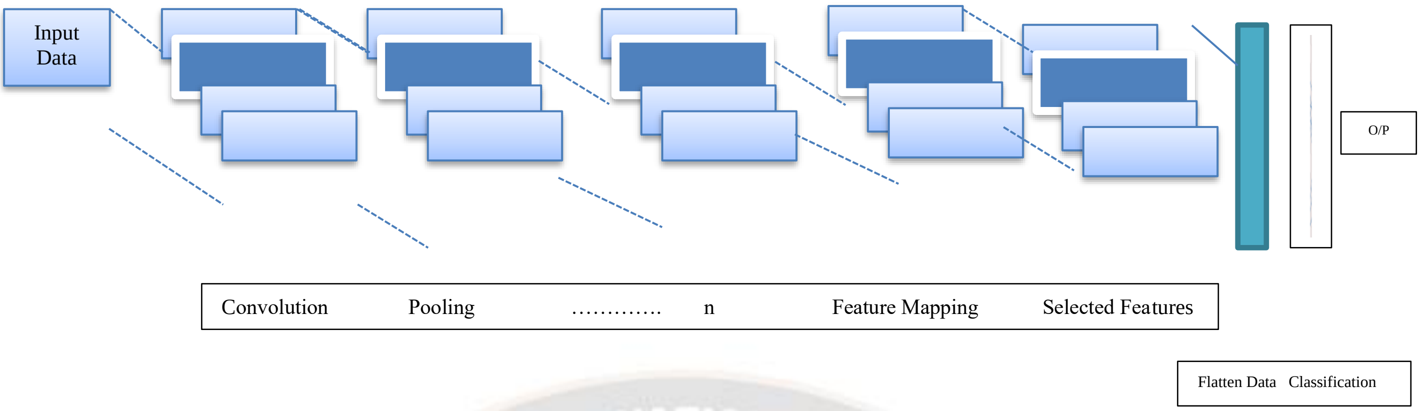

Figure 10. Architecture of CNN model

D. Tool Used

The proposed model was introduced on the OS window 10 with the processor of Intel(R) Core(TM) i7-10870H CPU @ 2.20GHz 2.21 GHz with RAM 16.0 GB . The research framework was developed using MATLAB 2018a.

E. Parameters

It computes and compares precision , error rate, etc. with existing classification techniques with various test cases to prove proposed enhancements.

Formulas:

Recall: It is defined as the ratio of true positive ($true_{pos}$) and sum of $true_{pos}$ and false negative ($false_{neg}$). It is formulated as

$$\text{Recall} = \frac{true_{pos}}{true_{pos}+false_{neg}} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(iii)}$$

Precision: It is defined as the ratio of true positive ($true_{pos}$) and sum of $true_{pos}$ and flase positive ($false_{pos}$). It is formulated as

$$\text{Precision} = \frac{true\_pos}{true_{pos}+false\_pos} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(iv)}$$

MSE= It is defined as the ratio of the number of data points and square by the value returned by the model (kj) subtract the actual data points (kj). It is formulated as;

$$\text{MSE} = \frac{1}{n}\sum_{j=1}^{n}(kj - kj')^2 \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(v)}$$

Here,

MSE = mean square error rate; n = no. of data-points; kj= observed; and kj' = predicted values.

FAR= It is defined as the ratio of $false_{neg}$ and sum of true positive ($true_{pos}$) and false negative ($false_{neg}$) values. It is formulated as;

$$FAR = \frac{false_{neg}}{true_{pos}+false_{neg}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(vi)}$$

FRR= It is described as the ratio of false positive ($false_{pos}$) and addition of false negative ($false_{neg}$) and false positive ($false_{pos}$) values. It is formulated as;

$$FRR = \frac{false\_pos}{false_{neg}+false\_pos} \ldots\ldots\ldots\ldots\ldots\ldots\text{(vii)}$$

IV. Result And Discussion

The researched OMFA-CNN model simulations were developed using GUIDE framework, GUI interface, and MATLAB script programming language. It used the firefly optimizer, default learning rate (LR), and loss function. The outcomes of the implemented OMFA-CNN model main focused on;

- Discriminating the PL images into healthy, virus, insect bite, etc.
- Calculation of the implemented OMFA-CNN model performance on the potato leave disease dataset using preprocessing methods on the training set.
- OMFA-CNN model presentation on the online available dataset Kaggle (Plant Village) by applying pre-processing methods.
- The research work developed PCA and GLCM feature extraction method used to extract the reliable feature sets.
- It calculated the performance of the implemented model on the PL disease dataset.
- To compare the outcomes with other methods like Mask RCNN [11].
- To calculate the outcomes of PLDD system with existing analyses using DL methods.

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The experiment was conducted to evaluate the performance of the proposed OMFA-CNN model. The research work employed four different data preprocessing methods on the training set of the potato leaf disease dataset. All simulations utilized the firefly optimizer, loss function, 100 epochs, and default LR. The proposed model metrics are shown in Table IV such as recall value of 99 %, and precision value of 99.3 percent. Table V represents the comparison analysis between proposed model and existing models such as Mask RCNN [11] and others.

TABLE IV. PERFORMANCE METRICS WITH DIFFERENT CATEGORIES

Parameters	Recall (%)	Precision (%)	FAR	FRR	MSE
OMFA-CNN Model	99	99.3	0.006	0.00009	4.014

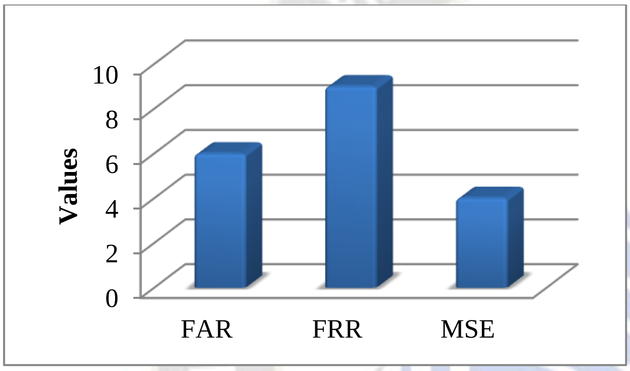

Figure 11. Error rate in form of (FRR, FAR, and MSE)

Figure 11 shows the performance of the error rate values in form of FAR, FRR, and MSE values. The proposed model has reduced the error rate values as compared with the existing model.

TABLE V. COMPARISON ANALYSIS

Models	Recall	Precision
OMFA-CNN	99	99.3
Mask-RCNN	86	97
KNN	93.8	93.8
SVM	93.8	94.1
NN	95.3	95.3
Logistic regression	97.8	97.8

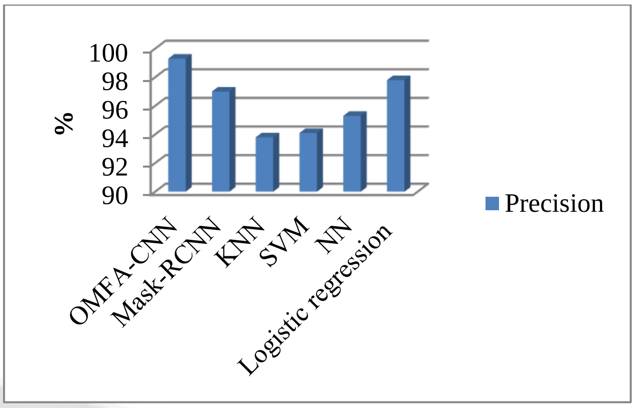

Figure 11. Comparison analysis with different models: Precision (%)

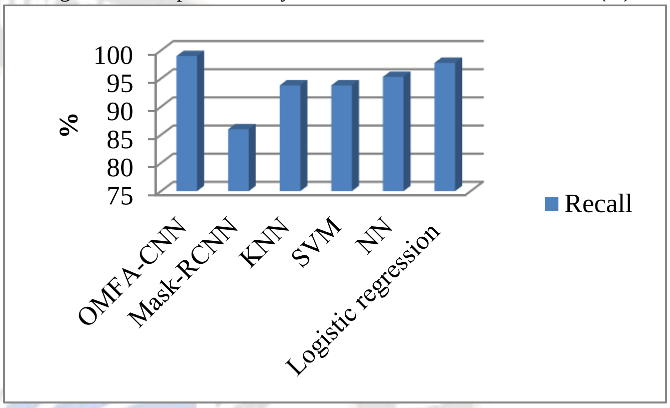

Figure 12. Comparison analysis with different models: Recall (%)

Figure 11 and 12 represent that the precision for our model is 99.3% and recall for our model is 99% which defines an accurate accuracy of our classification. These figures show the comparative analysis of the different classification models such as OMFA-CNN, Mask-RCNN, KNN, SVM, NN, and LR with precision and recall. The proposed model has improved the precision and recall rate as compared with the existing models.

V. CONCLUSION AND FUTURE SCOPE

The proposed work has used the concept of DL and has established an automatic system to detect and classify the diseases in PL such as healthy, insect bite, virus, etc., with novel OMFA-CNN model attain classification precision value of 99.3 percent, and recall value of 99 percent. OMFA-CNN model can help farmers in classifying diseases in their early phases and in improving their crop yields. In this analysis, a rapid and straightforward OMFA-CNN model for PL disease detection was implemented to classify the PL diseases. It extracted the PLs from the potato plant images at the different level using preprocessing methods, image segmentation method, feature extraction method, and then implement OMFA-CNN proposed model to detect potato leave diseases. At the similar time, it considered the effect of the environmental factors on PL diseases. OMFA-CNN method performed importantly well on the PL images gathered form Kaggle (Plant Village). Simulation analyses were conducted on Kaggle (Plant Village) dataset with different pre-processing techniques, features extraction and selection methods. The presentation of the researched OMFA-CNN method was also calculated in the Plant Village dataset, where the implemented method outperformed the other techniques. The implemented method performance was compared with different methods including Mask RCNN [10] method used for PL disease detection. The proposed OMFA-CNN model has achieved precision value of 99.3 percent, and recall value of 99 percent. It achieved high precision and recall rate as compared with existing models.

Future work will extend to several categories of disease detection on a single leave and to localize the diseases, improve the potato leave disease database, introduce internet of things (IoT) based real time monitoring system, develop an automatic website and launch a mobile app. It will calculate the time and speed parameters.

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