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Enhanced Convolutional Neural Network Model for Cassava Leaf Disease Identification and Classification

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Abstract: Cassava is a crucial food and nutrition security crop cultivated by small-scale farmers and it can survive in a brutal environment. It is a significant source of carbohydrates in African countries. Sometimes, Cassava crops can be infected by leaf diseases, affecting the overall production and reducing farmers' income. The existing Cassava disease research encounters several challenges, such as poor detection rate, higher processing time, and poor accuracy. This research provides a comprehensive learning strategy for real-time Cassava leaf disease identification based on enhanced CNN models (ECNN). The existing Standard CNN model utilizes extensive data processing features, increasing the computational overhead. A depth-wise separable convolution layer is utilized to resolve CNN issues in the proposed ECNN model. This feature minimizes the feature count and computational overhead. The proposed ECNN model utilizes a distinct block processing feature to process the imbalanced images. To resolve the color segregation issue, the proposed ECNN model uses a Gamma correction feature. To decrease the variable selection process and increase the computational efficiency, the proposed ECNN model uses global average election polling with batch normalization. An experimental analysis is performed over an online Cassava image dataset containing 6256 images of Cassava leaves with five disease classes. The dataset classes are as follows: class 0: "Cassava Bacterial Blight (CBB)"; class 1: "Cassava Brown Streak Disease (CBSD)"; class 2: "Cassava Green Mottle (CGM)"; class 3: "Cassava Mosaic Disease (CMD)"; and class 4: "Healthy". Various performance measuring parameters, i.e., precision, recall, measure, and accuracy, are calculated for existing Standard CNN and the proposed ECNN model. The proposed ECNN classifier significantly outperforms and achieves 99.3% accuracy for the balanced dataset. The test findings prove that applying a balanced database of images improves classification performance.

Keywords: convolutional neural network model; ECNN; deep neural network; cassava leaf disease identification; global average election polling layer

1. Introduction

Cassava is the main crop in Africa and many other nations. Africa is the largest producer of Cassava crops. Cassava can be cultivated successfully in any climate, including drought and unproductive soil. Cassava crops encounter several challenges during production, i.e., leaf diseases and poor quality. Cassava leaf diseases are the principal cause of production reduction, and they can directly affect farmers' revenue [1].

Cassava leaf disease identification must be treated on a priority basis to improve production capacity. The automatic detection of crop diseases focused on crop leaves is critical in crop production. Furthermore, effective and accurate detection of leaf diseases significantly affects crop productivity improvement. Cassava leaf diseases are similar to Maize leaf diseases [2].

Early recognition of leaf disease facilitates the rescue of cultivars well before the plant can be infected permanently [3]. A few researchers focused on building fusion plants resistant to pathogenic organisms and created a system to recognize and anticipate crop disease formation from leaf images [4].

Farm owners can significantly raise farm yields by using smart farming. Farmers spend a lot of time, money, and effort in the manual identification of plant diseases, and the results are still inaccurate. Research [5] has developed an intelligent system based on image classification and deep-learning methods.

A deep-learning and machine-learning-based model is discussed in research [6] for leaf disease detection. The automated machine-learning model for detecting and treating Cassava crop diseases enables farmers and experts to increase system throughput and accuracy. Deep-learning-based CNN classifiers can enhance leaf disease detection in all the possible situations where image-based diagnostics with advanced training are involved. Various portable devices are also used in leaf disease detection.

In all the instances where an intelligent classifier is installed on portable devices and contains a novel disease, datasets can enhance detection accuracy. Portable devices, i.e., smartphones, drones, and laptops, can be easily tested in realistic scenarios [7].

Researchers have considered various novel techniques to resolve leaf disease detection issues, i.e., image classification, AI, machine learning, and deep learning [8]. Data preprocessing is an essential phase in image analysis, which includes various processes, i.e., image optimization, color adjustment, reshaping, and feature extraction. An image classification method must be applied with an image enhancement technique for better outcomes [9].

A hybrid deep-learning and image-classification-based model for leaf disease detection is discussed in [10]. However, these existing research works have several challenges, which need immediate attention. This motivates researchers to work on Cassava leaf disease detection [11]. These factors also encourage researchers to develop a more robust and reliable Cassava leaf disease detection system.

This research aims to fill the gaps by presenting a better overview of leaf disease detection and analysis in Cassava plants. This research provides a comprehensive learning strategy for real-time Cassava leaf disease identification based on enhanced CNN models (ECNN). The main contributions of this research are as follows:

- This research presents a complete overview of Cassava leaf diseases.
- This research presents a detailed overview of the CNN model and describes how the CNN model can improve Cassava leaf disease detection.
- The existing Standard CNN models [12] utilize a complex set of features and a massive computational overhead. To overcome these issues, in the proposed model, we upgraded the traditional convolution network model by adding new features.
- The proposed ECNN model utilizes a depth-wise separable convolution, which minimizes the feature count and computational overhead.
- The proposed ECNN also utilizes a distinct block processing feature to process imbalanced images.

- Furthermore, the proposed ECNN model utilizes de-correlation stretching with Gamma correction. It enhances the image color segregation feature and provides a higher band-to-band correlation.
- The proposed model utilizes a global average election polling layer to replace the fully connected layer to decrease the number of variables. After that, ECNN utilizes a batch normalization layer that enhances the overall computational efficiency [13].
- The proposed ECNN method is validated by calculating the standard performance measuring parameters, and the results are compared with the existing Standard CNN method.

The research article is organized as follows. Section 1 covers introductory work related to the research; Section 2 covers related positions in Cassava leaf disease identification and classification. Next, Section 3 covers materials and methods related to research. Section 4 covers the proposed ECNN model's implementation, results, and discussion. Section 5 covers the conclusion and future work.

2. Related Work

Cassava is the most popular commercial and industrial crop in Africa and Thailand. Due to the apparent pleasant environment and soil, it is primarily produced in these countries. Cassava crop encounters several issues, i.e., leaf disease and fungal infection, thus reducing production and increasing cost. Early and accurate detection of Cassava leaf disease is a promising research area for researchers. Various research articles suggest different methods and models to improve Cassava leaf disease detection. Existing research has also tried to determine effective methods for improving Cassava crop production. This section covers the existing research on Cassava leaf disease detection.

2.1. Machine Learning Based

ResNet-50- and SVM-classifier-based Cassava leaf disease model is presented in [14]. The proposed model first extracts all the relevant features and then classifies the image dataset using an SVM classifier in the next phase. The outcomes show better accuracy and performance by incorporating ResNet-50 and SVM classifiers.

A digital image processing model uses a hybrid transfer learning method [15]. It is crucial to perform correct data preparation in leaf disease research. This improves plant disease pattern recognition, forecasting, and model performance.

A hybrid model based on SVM and RF for Cassava leaf disease detection is presented in [16]. The proposed model utilizes multiple feature selection processes, including selecting image type, association in parameters, quality, and uniformity. The proposed classification model achieved more than 90% accuracy compared to the existing model.

The SVM and Naive Bayes machine-learning-based model is presented in [17] to detect plant diseases. The researcher suggested that a massive data history and machine-learning methods play an essential role in plant disease analysis. The machine-learning method [18] provides a valuable contribution to evaluate a considerable volume of leaf image data. Another research [19] presented a deep-learning-based model with ImageNet for Cassava leaf disease detection.

2.2. Leaf Shape, Colour, and Texture Based

Leaf disease detection based on leaf properties is discussed in research [20]. The proposed model utilized complex geometries and segmentation-based methods for feature extraction. After feature extraction, the SVM classification method was applied to classify leaf diseases. A shape- and texture-based classification for Cassava leaf disease identification is discussed in research [21]. The proposed model achieved more than 84% accuracy and 88% detection rate.

A region-based detection method is discussed in research [22]. This work mainly focused on retrieving Cassava leaf properties using a cluster center method. A bacterial and viral infection detection algorithm is introduced in research [23]. The proposed method first

detects leaf image texture and shape features, enhancing disease classification outcomes and improving overall precision and accuracy.

An innovative procedure for categorizing plant leaf disease is discussed in research [24]. Often, these plants have distinctive leaves that vary by features, such as margin, color, shape, and texture. A shape-, color-, and texture-based leaf disease classification are discussed in research [25]. This research classified diseases using combinations of two and more characteristics, such as shape, size, color, and texture. In the proposed method, a shape-based technique first extracts the curve receipt using leaf stem and afterward determines the inconsistencies using a Jeffrey divergence estimate method. Leaf disease detection based on computer vision and leaf feature analysis method was discussed in research [26].

2.3. Neural Network Based

A deep-learning-based model to analyze Cassava leaf diseases is presented in research [27]. This proposed model firstly performs a subdivision method and later applies a classification approach to diagnose Cassava leaf disease. GoogleNet- and AlexNet-based convolutional neural network structures were discussed in research [28] to analyze and identify distinct CNN leaf diseases.

A neural-network-based Cassava leaf disease prediction model is described in research [29]. This research utilizes various neural network models on different crops to analyze diseases and infections. Experimental results show the strength of the proposed model through higher recognition rates. A deep-learning-based model is described in research [30] to predict leaf disease. This research utilizes a feature selection method to recognize thirteen particular crop diseases. Researchers have trained CNN architecture by utilizing the Caffe deep-learning approach.

An improved deep-learning-based model is described in research [31] to predict leaf disease classification. This research work also covers the limitation of existing works. A nine-layer-based convolutional neural network model is presented in [32] to characterize Cassava diseases in plants.

A NASNet-based fully convolutional architecture is described in research [33]. This model applied a feature selection model to recognize fungal leaf infection. The proposed model achieved an accuracy rate of 94.1% compared to an existing model. A superficial CNN model is presented in research [34] to identify and characterize plant leaf diseases. In the initial phase, researchers retrieved the leaf features using the feature extraction method and then categorized them using a feature selection method with random forest classification methods.

2.4. Comparative Analysis

Table 1 represents the comparative analysis of various existing methods used in plant leaf disease detection and analysis.

Table 1. A Comparative Analysis of Various Existing Research Works.

Reference	Dataset	Technique/Model	Outcomes
[35]	Online Cassava Leaf disease dataset	DRN (Deep Residual Neural) Network	Precision 94.24% and AUC 90.1%
[36]	Online Cassava Leaf disease dataset	Random Forest, SVM and SCNN (Shallow CNN)	Detection rate 91.7% and Time 89.6%
[37]	Online Cassava Leaf disease dataset	9-Layered CNN Model	Accuracy 90.48%
[38]	Online Cassava Leaf disease dataset	FR-CNN (Faster Recurrence CNN)	Specificity rate 77.8%, Precision rate 91.8%, and Sensitivity rate 73.26%
[39]	Online Cassava Leaf disease dataset	SSD (Single Sot Multi-box Method)	Precision rate 90.8%

Table 1. *Cont.*

Reference	Dataset	Technique/Model	Outcomes
[40]	Online Cassava Leaf disease dataset	MNet (Mobile Net Detector) Model	Accuracy 89.41% and Sensitivity rate 76.96%
[41]	Online Cassava Leaf disease dataset	GoogleNet and AlexNet CNN Model	Precision 87.9, Recall 86.58, and F-measure 81.47%
[42]	Online Cassava Leaf disease dataset	Machine-learning methods SVM, Naïve Bayes	Sensitivity rate 0.798, Specificity rate 0.756, and AUC rate 0.875
[43]	Online Cassava Leaf disease dataset	CNN model	Accuracy 93.5, Precision 91.9

3. Materials and Methods

This section covers the proposed model architecture and working steps.

3.1. Proposed ECNN Architecture

This research provides a comprehensive learning method for real-time Cassava leaf disease detection based on an enhanced CNN model (ECNN). The existing Standard CNN model is based on extensive features and a massive computational process that increases the computational overhead. We present an enhanced CNN model (ECNN) for Cassava leaf disease detection and an analysis for overcoming these issues. The existing Standard CNN model is improved by adding new features and properties.

In the proposed ECNN model, a depth-wise layer separation feature is introduced, minimizing the feature count and computational overhead. Additionally, a global average election polling layer replaces the fully connected layer and decreases the variable count. Then, a batch normalization layer is applied to adjust computational efficiency. The proposed ECNN model utilizes a distinct block processing feature to deal with data imbalance. The next phase utilizes de-correlation stretching with Gamma correction feature, which improves color segregation with high band-to-band correlation features on the image dataset.

The architecture of the proposed ECNN model involves three convolutional layers and four fully integrated layers in the head. The first layer contains 32 (5×5) convolutions, in order to know and understand more significant characteristics of workflow normalization. This layer also contains batch sizes of (3×3) for the max-pooling feature. The subsequent two and three layers consist of two main pairs of convolution layers. They mainly contain 64 features, with size (3×3) batch normalization features. They also contain 128 features of size (3×3) for max pooling, respectively. The layers are arranged in a particular manner to facilitate the entire learning system to learn broader and deeper characteristics by applying the stacking of two pairs of convolution layers. Figure 1 shows the architectural features of the proposed ECNN framework.
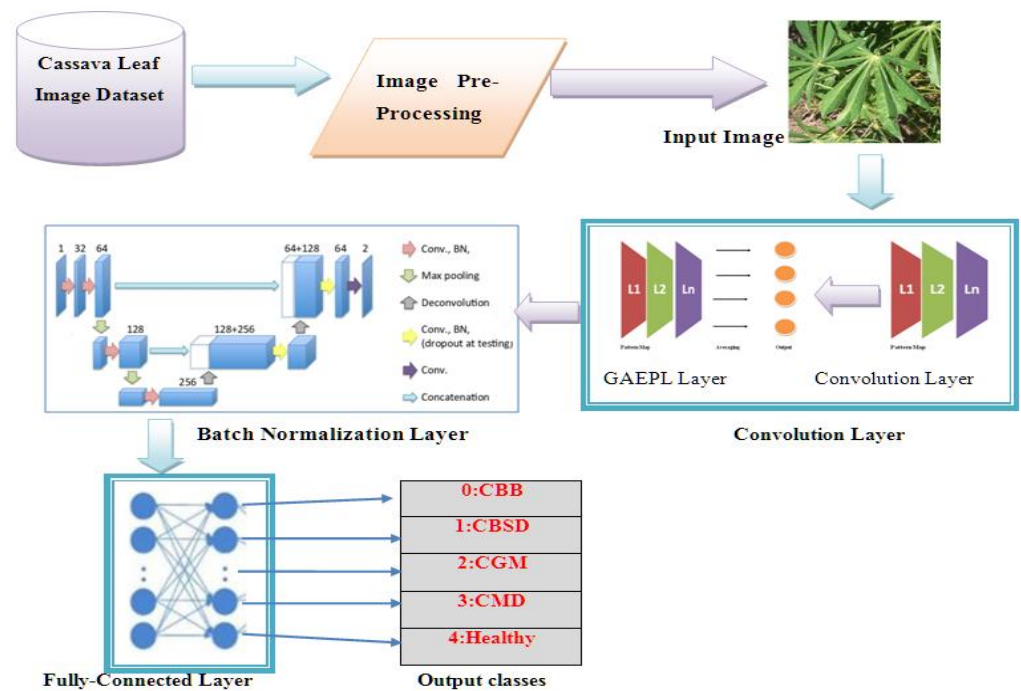
Figure 1. Architecture of Proposed ECNN Model.

3.1.1. Global Average Election Polling Layer (GAEPL)

GAEPL's objective is to standardize the entire network structure and minimize the dimensionality from three-dimensional to one-dimensional, which minimizes the overfitting issues. The proposed ECNN model utilizes the pattern map feature within the last CNN layer to aggregate all the outputs into a sequence of one-dimensional form. After applying a GAEPL, the number of variables is considerably reduced because the advancement of pattern maps in matrices is not required, as described in Figure 2.

Figure 2. Global Election Polling Layer.

The advantage of a GAEPL over the convolutional layers is that it can effectively maintain the multilayer architecture by improving the connection between the pattern maps and analogies. It also provides more convincing features and well-understood pattern map classifications [44].

A pooling function includes sliding a two-dimensional filtration system across each link of its feature space. It also aggregates all the features within the filter's communication range. For a convolution layer feature space composed of parameters (Nw: width of feature space, Nh: height of feature space and Nc: Total number of channels/links in a feature space, f: filter size, and s: length of stride), the measurement of results acquired straight after a pooling layer can be defined as

$$[(Nh - (f + 1)/S) \times (Nw - (f + 1)/s) \times Nc] \qquad (1)$$

Each link in the feature space is combined into a single value using the global pooling layer function. As a result, the (Nh × Nw × Nc) feature space is adjusted to (1 × 1 × Nc). It is the same as using only a filter with aspects (Nh × Nw), i.e., the feature map's elements.

3.1.2. Batch Normalization Layer (BNL)

BNL is a training method for complex CNN architecture. It standardizes the number of parameters at each level in small batches. It also improves the teaching methods and significantly minimizes the training epochs needed to build deep convolutional networks. Figure 3 shows the working of BNL [45].
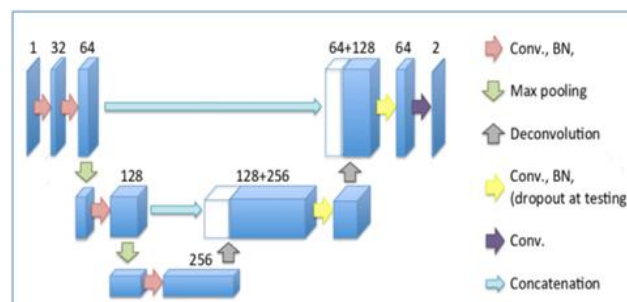

Figure 3. Batch Normalization Layer in ECNN.

In CNN, the quantity of neurons in each layer is often expansive. If data transmission at a specific layer starts shifting from one layer to another, the network size also grows, enhancing the modeling risks. Consequently, a batch normalization process mainly aims to relieve the above issues. A batch normalization process splits the population into small clusters and fixes each cluster's variables [46]. A record inside one cluster collectively depends on the direction of the differential and minimizes unpredictability when the value decreases. A CNN group requires fewer items than a complete dataset during the process, which dramatically reduces the computation count. An activation function is used in the batch normalization process. Before applying an activation function, the batch normalization layer normalizes the input data toward all the levels and overcomes the problem of addressing the input offset. A batch normalization process transforms the input n as per the following formula given in Equation (2):

$$BN(n) = \beta + \gamma + \frac{n - \mu\beta}{\sigma\beta} + \beta \tag{2}$$

where $n \in B$ represents an input element toward batch normalization (BN), which is mainly related to a small batch β, γ represents the scale variable, $\sigma\beta$ represents the standard deviation, and $\mu\beta$ represents the sample mean value.

3.1.3. Distinct Block Processing (DBP)

This research utilized an imbalanced Cassava leaf disease dataset. The data are biased against CBSD, CBD, and CGM disease classes, and they also include Cassava leaf images of varying sizes. The imbalanced dataset needs immediate attention, and it should be converted into a balanced dataset for better outcomes. A distinct block technique is used to fix this problem. Therefore, when the resolution of the source image is significantly greater than the neural network's potential, the block processing method is utilized [47].

On the other hand, the block processing method enables the preservation of visual information. It has earlier been utilized effectively in numerous computer-vision-based research works. The input data are filtered from block to block during a distinct block operating condition. The input image is divided further into a rectangular shape, and each block is processed independently to evaluate the correlating block image outcome and define the image pixels. The images are separated into distinct blocks in the top left corner. A zero-padding value is introduced to boost the series of images in less identified

classes, and the blocks do not align to a particular object. All Cassava leaf disease class labels contain similar images for all five classes. Different block processing methods boost each class's feature count.

3.2. Working of Proposed ECNN

The Cassava leaf disease detection and analysis using the proposed ECNN model includes various phases. Each phase has its distinct features. The max-pooling layer's goal is to decrease the geographic capacity dimensions of all image pixels. After parameter selection and improvement with the grid search process, the network's head comprises four fully linked layers of 512 neurons. The first, second, and third layers contain 1024 neurons in this process, and the fourth layer contains 256 neurons. There is a neuron for each classification in the output-based convolutional layers correlating to five Cassava leaf disease classes. The dropout feature is utilized in the fully inter-linked layers to overcome inaccuracy and overfitting issues. In particular, the fully connected layers obtain essential information from the object through the fully connected components. To utilize these selected features to identify and classify all the healthy and unhealthy classes from the leaf images, the convolution layer value can be measured as Equation (3)

$$x_k^l = f\left(\sum_{i\,\varepsilon M_k}^{n} x_j^{l-1} \begin{pmatrix} n \\ k \end{pmatrix} * x_{jk}^l + a_k^l \right) \tag{3}$$

where x_j^{l-1} represents the feature map value of the last layer used as an output, x_k^l represents the channel output value, n represents the layer number, a_k^l represents the offset value related to channel, M_k represent the subset data for input.

3.2.1. Phase 1

The first phase performs image transformation, including mask segment, deskew, gray, thresh, rnoise, canny, and sharpen. Then, to remove image imbalance, we apply a pre-processing data phase based on Contrast Limited Adaptive Histogram Equalization (CLAHE) method [48]. Figure 4 shows image transformation. Here, one to ten transformations are performed by various methods. In Figure 4: (1): original, (2): mask, (3): segment, (4): deskew, (5): gray, (7): thresh, (8): rnoise, (9): canny, and (10): sharpen.
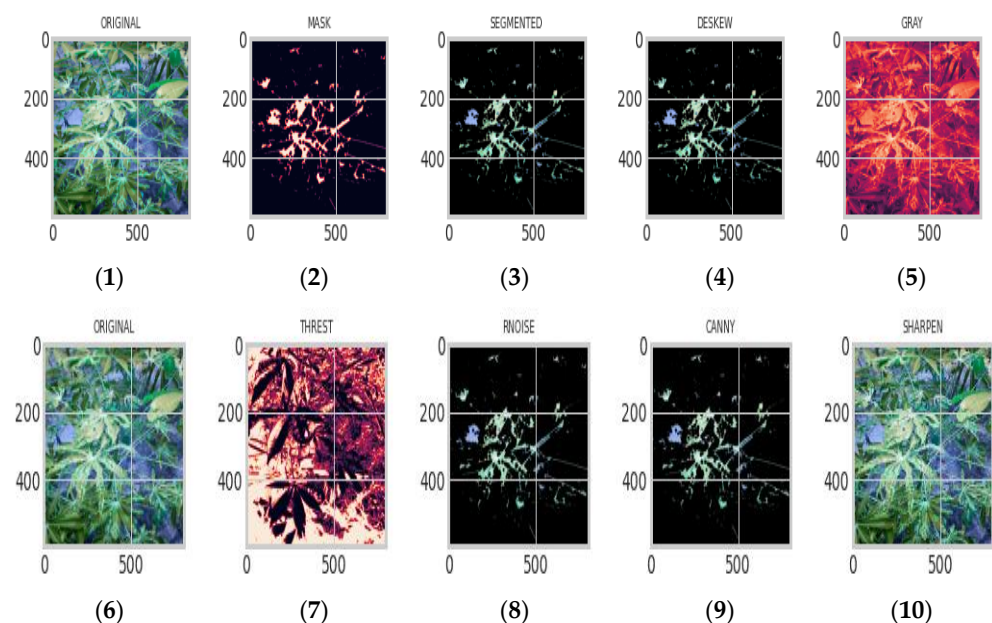

Figure 4. Image Transformation (Image (**1**,**6**): Original, (**2**): Mask, (**3**): Segment, (**4**): Deskew, (**5**): Gray, (**7**): Thresh, (**8**): Rnoise, (**9**): Canny, and (**10**): Sharpen).

Figure 5 shows the image pre-processing by using the CLAHE method. The CLAHE method improves the performance of image processing methods in low-resolution and low-contrast environments. The initial color image is transferred from RGB to Y.I.Q. and H.S.I. shared spaces. In the next phase, a CLAHE method is utilized in the Y.I.Q. and H.S.I. color spaces to produce two improved image datasets. Then, the Y.I.Q. and H.S.I. improved images are subsequently converted to RGB color space.
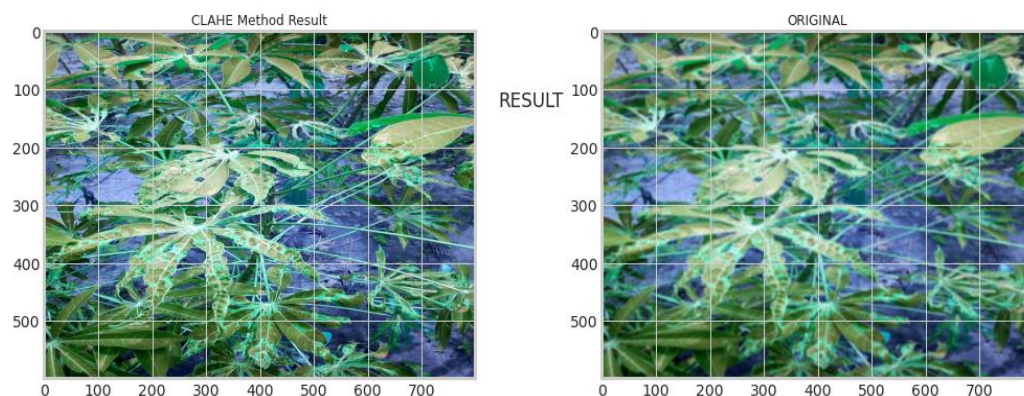

Figure 5. Image Pre-Processing Model Based on CLAHE.

3.2.2. Phase 2

In this phase, we applied the SMOTE method for resampling purposes [49]. The first phase mainly removes the skewness from the images. As discussed, the Cassava leaf disease dataset [50] that we are using for this research is highly imbalanced. The second phase utilized a perfect combination of existing methods: SMOTE (Synthetic Minority Oversampling Technique), class-weight, and focal loss techniques, to enhance the volume of the training dataset, which led to improvements in high precision. SMOTE is a method for oversampling that generates data samples only for class labels. This method mainly overcame the overfitting issue caused by arbitrary data.

The SMOTE method creates unique Cassava leaf disease data samples based on actual results to remove the skewness. The SMOTE approach selects samples in the feature space closest to them, makes a clear distinction between them in the subspace, and draws a new sample once at the position along each path.

3.2.3. Phase 3

Phase three is mainly applied to enhance the size of the Cassava leaf image dataset. To address the issue of a limited dataset, this phase utilizes dataset enhancement techniques, such as random shearing, image flipping, center zooming, random scaling, height/width shift, and random cropping. This phase also utilizes an image-flipping method, which increases the dataset volume. It helps in the testing and training process and provides better precision, accuracy, and performance.

4. Results and Discussion

This section covers the implementation, dataset description, result comparison, and discussion. The python programming language implements existing Standard CNN [2] and proposed ECNN methods. The proposed ECNN model is compared with the existing Standard CNN architecture-based model. To implement these models, we are using a similar type of feature. Various performance measuring parameters are calculated, i.e., precision, recall, f-measures, and accuracy.

4.1. Dataset

The Cassava leaf dataset is collected from the online Kaggle dataset [50]. The original data contain 6256 Cassava leaf images with imbalanced occurrences of 316 healthy Cassava leaves. The dataset also contains the four types of unhealthy infected Cassava leaf classes.

Figure 6 shows the various disease classes of Cassava leaf (0: CBB, 1: CBSD, 2: CGM, 3: CMD, and 4: Healthy).

Figure 6. Healthy and Unhealthy Cassava Images.

Different parameters are calculated to examine the performance of the proposed ECNN model, i.e., dropout, batch size, other numbers of epochs and precision, recall, f-measure, accuracy.

4.2. Data Pre-Processing

In the pre-processing phase, the raw Cassava images are normalized. An imbalance is also removed from the images. The image set is classified into two main categories: standard (healthy) and abnormal (unhealthy). These natural-color images are divided into five binary classes, from 0 to 4. The unhealthy Cassava images are classified into distinct classes. The complete normalization process in data pre-processing for a data sample is described in the Equations (4)–(6):

$$(\gamma)^n = \frac{1}{n} * \sum_{k=0}^{n} N_k \tag{4}$$

$$(\mu)^2 = \frac{1}{n} * \sum_{k=0}^{n} (N_k - \gamma) \tag{5}$$

In Equations (4) and (5), N_k shows the data for a pixel, which is stored at position k, and *n* shows the pixel samples. γ shows the mean data value, and $(\mu)^2$ shows the variance. Based on Equations (4) and (5), a normalization process can be defined by Equation (6) as follows:

$$N^| = \frac{N_k - \gamma}{(\mu)^2 + \varepsilon} \tag{6}$$

In Equation (6), the $N^|$ represents the normalization value for an ith pixel, and ε is some small random value, where $\varepsilon > 0$.

In Cassava leaf image data pre-processing, the images' R, G, and B components are decreased from their mean values in the normalization progressive enhancement de-averaging. Moreover, there are a variety of issues with the Cassava leaf dataset. The first is

the small dataset size, and the next is the poor contrast and resolution images. Another challenge is associated with the skewness in the class label. The top class contains 39.4% of this dataset, and the minor class contains 2.89% magnitude variations [51].

We focused on enhancing Cassava image contrast using the CLAHE method. The CLAHE method can significantly improve the performance of image processing methods in low-resolution and low-contrast environments. To increase the size of the database, various image enhancement methods, i.e., random shearing, image flipping, central zooming, random cropping, random scaling, shifting of image height and width, are used. An image flipping method that helps to enhance the size of the database helps in training and validation for testing results.

In the next phase, all the Cassava leaf images are restructured into (224 × 224) by adjusting the width and length of the images. The images of leaf categories are restructured further into vertically and horizontally flipped components. The Cassava image dataset includes CMD: 2808, CGM: 923, CBB: 166, and CBSD: 1593 images. As shown in Figure 7, these images are completely unbalanced, with a heavy bias toward CBSD and CMD Cassava disease classes.
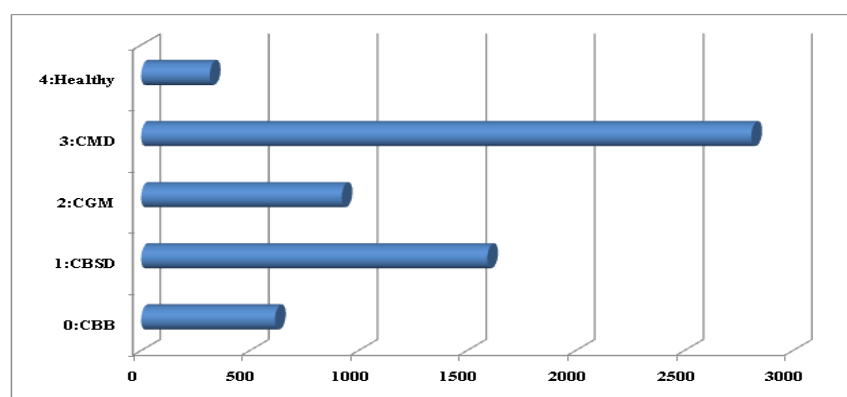

Figure 7. Cassava Leaf Dataset.

4.3. Visualization of Proposed ECNN Model

The proposed ECNN model generates 239 NN layers. Figure 8 represents the visualization outcomes of the first five layers (layer 1 to layer 5) of the proposed ECNN model. Layer 1 represents the input image; layer 2 represents the rescaling process; layer 3 represents normalization; layer 4 represents the stem_conv_pad; and layer 5 represents the stem_conv. The proposed ECNN model's structure consisted of three convolution operations and a core of four fully linked layers.

Layer 1 contains 32 cores (5 × 5) for learning higher batch normalization characteristics, with max pooling of (3 × 3) pool capacity. Layers 2 and 3 contain two fully connected layers with 64 (3 × 3) and 128 (3 × 3) feature selection, batch normalization, and max pooling. A batch normalization process enables the creation of the batches for two different sets of convolution layers. Before completing the max-pooling process, all the layers are structured to enhance the learning of the entire model. In the ECNN layer architecture, layer 4 shows the "stem_conv_pad", which describes the Keras Zero Padding 2D normalization process outcomes, and similar layer 5 shows the "stem_conv", which describes the Conv2D in Keras outcomes [52].
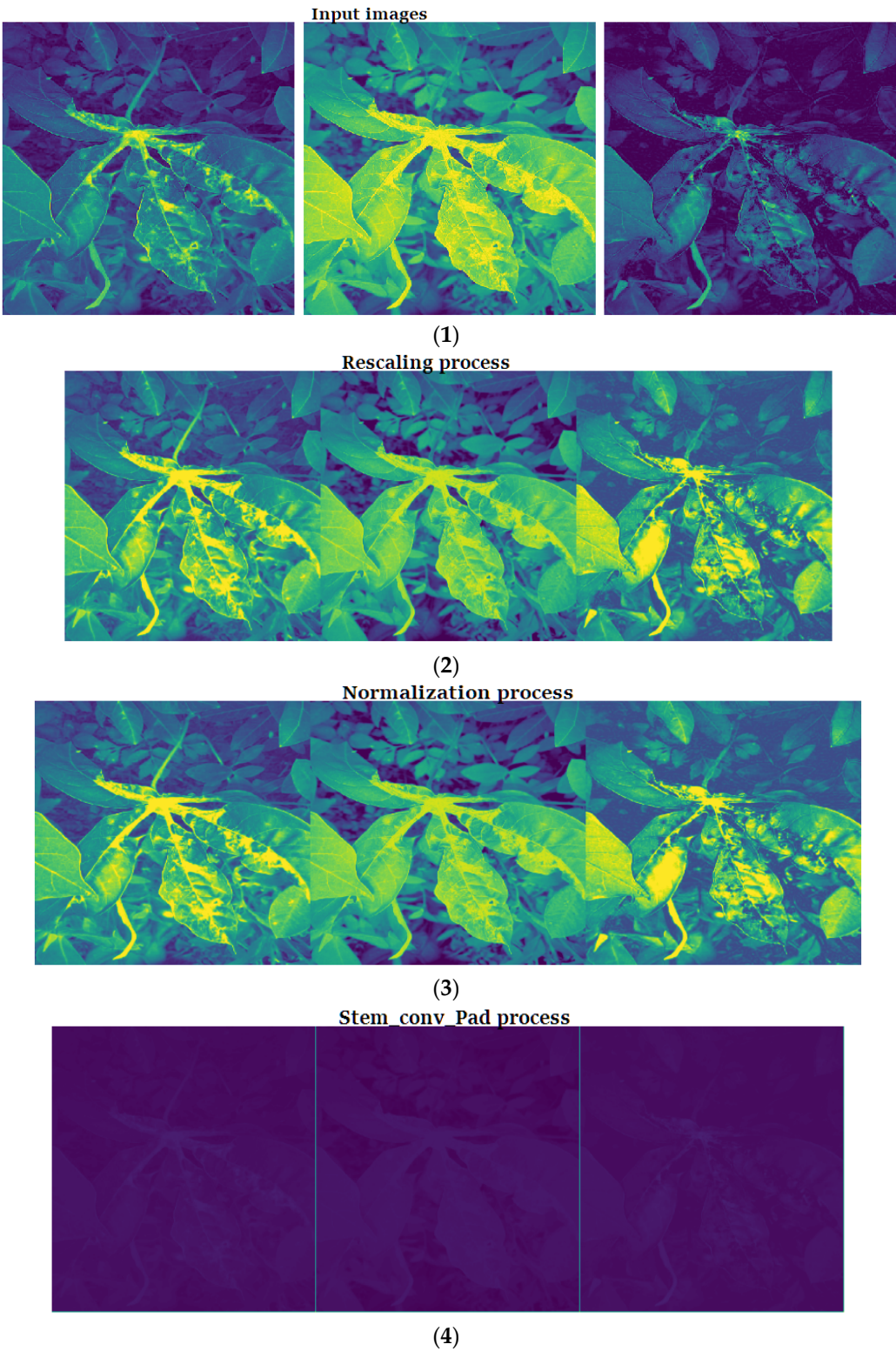
Input images
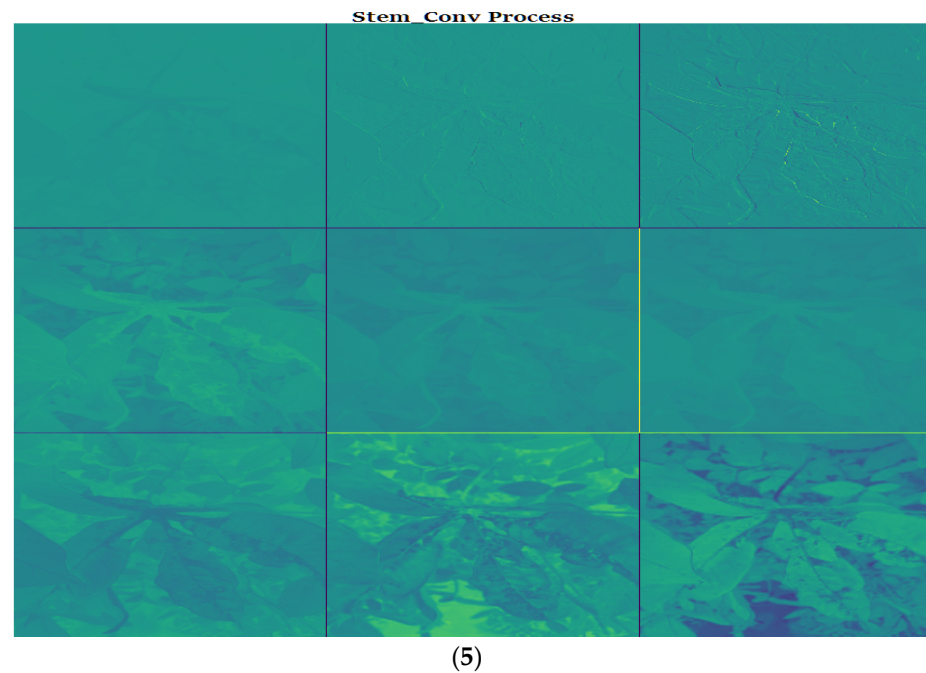

(**1**)

Rescaling process

(**2**)

Normalization process

(**3**)

Stem_conv_Pad process

(**4**)

Figure 8. *Cont.*

Figure 8. Layered Visualization of Proposed ECNN Model ((**1**) Layer 1: Input, (**2**) Layer 2: Rescaling, (**3**) Layer 3: Normalization, (**4**) Layer 4: stem_conv_pad, and (**5**) Layer 5: stem_conv).

4.4. Experimental Outcomes

The existing Standard CNN model and Proposed ECNN methods are implemented using python and Anaconda distribution in this research. The online Kaggle Cassava leaf dataset is used for analysis. The dataset is divided into training and testing sets.

Following performance measuring, the parameters are calculated to measure the performance of the proposed ECNN method given in Equations (7)–(11) [53–56]:

$$\text{Accuracy} = (TP + TN)/[(TP + TN + FN + FP)] \tag{7}$$

$$\text{Precision} = [TP/(FP + TP)] \tag{8}$$

$$\text{Recall} = [TP/(FN + TP)] \tag{9}$$

$$\text{F-Measure} = 2 \times [(\text{Recall} \times \text{Precision})/(\text{Recall} + \text{Precision})] \tag{10}$$

Confusion Matrix (CM) = the total of true and false forecasts is summarized with score values divided by class. It is the main factor here for a CM. $\tag{11}$

where TP = True positive rate, FP = False positive rate, FN = False Negative, TN = True Negative.

In this experiment, we used two scenarios for Cassava leaf disease analysis. In Scenario 1, experimental analysis is performed on the imbalanced dataset, and in Scenario 2, experimental analysis was performed on a balanced dataset. Accuracy rate, precision, recall, and F-measure parameters are calculated to evaluate the training and test competitiveness of the CNN and proposed ECNN models.

4.4.1. Scenario 1

The first scenario performs experimental analysis on an imbalanced Cassava leaf disease dataset. The dataset is divided into 60% for training and 40% for testing purposes. K-fold cross-validation is applied with k = 3 for training and testing to achieve a higher precision.

Figure 9 represents the experimental outcome of the proposed ECNN and CNN model for training and validation accuracy, and training and validation loss for imbalanced

datasets. The experimental results demonstrate that the proposed ECNN model achieved training and validation accuracy of 94.689% and a loss of 24.547%, which is better than the existing Standard CNN model results, showing training and validation accuracy of 89.754% and a loss of 36.414%.

Figure 9. Experimental Outcome of Proposed ECNN and CNN Model on the Imbalanced Dataset ((**a**) ECNN Training and Validation Accuracy, (**b**) ECNN Training and Validation Loss, (**c**) CNN Training and Validation Accuracy, and (**d**) CNN Training and Validation Loss).

Figure 10 represents the confusion matrix of the proposed ECNN model for various Cassava leaf disease classes. This matrix shows the results of actual vs. predicted data. The healthy class shows an accuracy of 99.64%, which is better than the other classes. The CMD disease class is showing poor outcomes, at 94.69%.

Figure 10. Confusion Matrix of Proposed ECNN Model for Imbalanced Dataset.

Figure 11 represents the experimental results of the existing Standard CNN model and the proposed ECNN model. This graph is plotted between accuracy% and epoch for training and testing. The proposed ECNN method shows better training and testing accuracy for all the epoch cycles, and at epoch 300, it shows more than 99% accuracy.
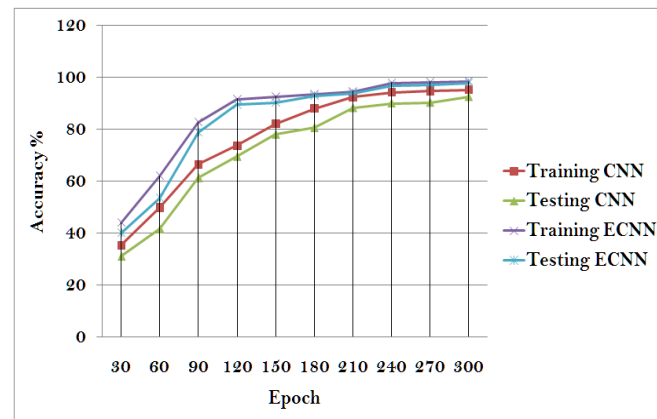

Figure 11. Accuracy Results for ECNN vs. CNN.

Tables 2 and 3 show the experimental outcomes for various Cassava leaf disease classes (0 to 4) for the proposed ECNN and CNN for the imbalanced dataset. These experimental results show that the proposed ECNN model performs better in accuracy, precision, recall, and f-measure than the existing Standard CNN model.

Table 2. Experimental Results for CNN Model for Imbalanced Dataset.

Class Type	Precision%	Accuracy%	Recall%	F-Measure%
CBB	81.256	83.659	82.224	82.154
CBSD	92.454	90.891	91.265	82.656
CGM	80.147	72.651	72.665	77.841
CMD	95.451	95.654	95.669	96.561
Healthy	70.981	68.961	69.781	69.874

Table 3. Experimental Results for ECNN Model for Imbalanced Dataset.

Class Type	Precision%	Accuracy%	Recall%	F-Measure%
CBB	91.021	92.568	84.565	84.998
CBSD	97.989	97.989	93.651	84.665
CGM	94.989	95.648	74.558	78.988
CMD	99.465	99.565	96.336	97.447
Healthy	96.981	97.778	90.145	91.407

4.4.2. Scenario 2

In the second scenario, the balanced dataset of the Cassava leaf is used. This dataset is divided into 60% for training and 40% for testing purposes.

Table 4 shows that the proposed ECNN procedure outperformed the existing Standard CNN model in terms of accuracy results for all the classes. The ECNN model shows 99.47% accuracy for CBB class, which is the highest in all the terms. Once we compare the experimental results of Scenarios 1 and 2, we can see that the proposed ECNN method shows better results for a balanced dataset than an imbalanced dataset.

Table 4. Experimental Results for CNN vs. ECNN Model for a Balanced Dataset.

Class Type	Accuracy%	
	CNN Model	**Proposed ECNN**
CBB	93.214	99.473
CBSD	91.478	98.132
CGM	89.981	99.391
CMD	93.124	98.924
Healthy	90.478	97.692

5. Conclusions and Future Work

Cassava leaf detection is a hot area of research. This research developed an ECNN model for a high imbalance Cassava leaf dataset to predict the disease class. The existing Standard CNN models utilize a higher extensive set of features and a massive computational process that increases the computational overhead. We upgraded the traditional convolution network model by adding enhanced features to overcome this issue. The proposed ECNN model utilizes a depth-wise layer separation, minimizing the feature count and computational overhead. Additionally, to overcome the dataset imbalance factor, this research applied improved data pre-processing methods. It reduces the error rate and improves image quality.

The proposed ECNN model is compared with the existing Standard CNN architecture-based model. To implement these models, we are using a similar type of feature. An experimental analysis was performed on an online Cassava leaf dataset. This dataset contained five classes: 0: CBB, 1: CBSD, 2: CGM, 3: CMD, and 4: Healthy. An experimental analysis clearly shows the strengthening of the proposed ECNN model in terms of better accuracy, precision, recall, and f-measure than the existing Standard CNN model.

In future work, we will try to improve the current research in various aspects: (a) the dataset can be improved in terms of data size and more disease classes; (b) the ECNN model can be improved by adding more CNN models in hybrid form; (c) the experimental analysis can be performed in a real-time environment with more performance measuring parameters.

Abbreviations

The following are the abbreviations used in this research:

CNN	Convolutional Neural network
ECNN	Enhanced Convolutional Neural network
CBB	Cassava Bacterial Blight
CBSD	Cassava Brown Streak Disease
CGM	Cassava Green Mottle
CMD	Cassava Mosaic Disease
SVM	Support Vector Machines
RF	Random Forest
DRN	Deep Residual Neural Network
SCNN	Shallow CNN
FR-CNN	Faster Recurrence CNN
SSD	Single Sot Multi-box Method
MNet	Mobile Net Detector Model
GAEPL	Global Average Election Polling Layer
BNL	Batch Normalization Layer
DBP	Distinct Block Processing
CLAHE	Contrast Limited Adaptive Histogram Equalization
RGB	Red Green Blue
YIQ	Y (perceived luminance), I, Q (color/luminance information) NTSC color model
SMOTE	Synthetic Minority Oversampling Technique
T.P.	True positive rate
FP	False-positive rate
FN	False Negative
TN	True Negative
NN	Neural Network
stem_conv_pad	Zero Padding 2D normalization
stem_conv	Conv2D

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