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# Applications Of Deep Learning Models For Image Object Recognition

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Image data analysis and processing to optimize the information is the classical research area. In addition, a number of applications available which are utilizing the image data. However, the techniques of data processing and analysis is changed significantly, due to the increasing size of image databases. In this context, deep learning is providing us the ability to deal with large image databases. In this paper, we are aimed to study and explore the deep learning techniques used for image data analysis and classification. Therefore, a review of the existing techniques has been carried out, which are based on deep learning. Additionally, an experimental analysis has been carried out between traditional image classification techniques and deep learning based architecture. By using this comparison, we are trying to identify the suitable image classification technique for developing a complete application. In this context, two variants of Convolutional Neural Network (CNN) is implemented. First, model has the configuration of two channel CNN and second model has the configuration of three channel CNN. The two channel CNN is trained using features extracted by Sobel Operator and Local Binary Pattern. Additionally, three channel CNN is trained directly utilizing the dataset color image color channels. The experiments has been conducted and performance for training and validation has been evaluated in terms of accuracy and loss. Further, class wise precision, recall, f-score and training time has been measured, which shows the three channel CNN configuration is 35% more efficient and 45% more accurate than two channel CNN configuration.

**Keywords**— Comparison, Deep learning, Image Processing, Image Databases, Machine Learning, Performance Analysis, Review.

## 1. INTRODUCTION

The image is one of the most attractive way of information representation. A set of values in form of a matrix is used to represent the real world objects. In form of color or black and white images [1]. Basically, black and white images are grayscale images and prepared by using the values between 0 and 255. These values are also known as pixels. In gray scaled images pixel values are representing the intensity of pixel. Similarly, in the color image a single pixel is defined by using the three values Red (R), Green (G) and Blue (B) [2]. The structure of information representation is different from other data format. Therefore, the techniques of image data analysis is different from other kind of data analysis task.

In this presented work, the aim is to explore the techniques of image analysis by using Machine Learning and Deep Learning techniques. Therefore, it is proposed to explore the recent contributions of the researchers for finding most popular techniques of image data analysis. By using the exploration of literature we are trying to recover the applications, algorithms, feature selection techniques, and dataset used for experimental analysis. Further for more detailed understanding of recent image processing technique a rice plant disease dataset has been considered. Additionally, the classification task has been performed using traditional machine learning technique and also with the help of deep learning technique. Additionally, their performance is computed and compared. This section provides an overview of the proposed work involved additionally the next section involve a brief review about the recently developed image based applications has been discussed.

## 2. LITERATURE REVIEW

In this presented work, the review is performed with the aim of exploring the different neural network architectures, which are used in analyzing the image based data. Therefore, a number of research articles have been collected using Google scholar. Additionally, tried to identify popular image based applications, Architectures that can help to improve the learning performance and Different pre-processing and optimization techniques to improve the performance of algorithms.

### 2.1 ABBREVIATIONS

This section is providing the keywords used in this paper. Table 1 shows the key abbreviations used.

**Table 1 Abbreviations**

| Abbreviations | Full form |
|---|---|
| AUCs | area under the curves |
| CLAHE | contrast limited adaptive histogram equalization |
| CNN | Convolutional Neural Network |
| DL | Deep Learning |
| FMCW | frequency modulated continuous wave |
| HPTI-v4 | Hyper-parameter Tuning Inception-v4 |
| KNN | k-nearest neighbour |
| LBP | local binary pattern |
| LSTM | Long Short Term Memory |
| ML | Machine Learning |
| MLP | multilayer perceptron |
| MRI | Magnetic resonance imaging |
| PCam | PatchCamelyon |
| RNN | Recurrent Neural Network |

| | |
|---|---|
| ROC | Receiver Operator Curve |
| SOM | self-organizing mapping |
| WSIs | Whole Slide Images |

## 2.2 ESSENTIAL CONTRIBUTIONS

This section is including the key contributions of the different image analysis techniques based on deep learning architectures.

**G. Pattarone et al [3]** were classifying breast cancer cells into live or dead, based on morphological characteristics of image. The classification can be performed. First, a vast image set composed by JIMT-1 human breast cancer cells that had been exposed to a chemotherapeutic drug treatment or vehicle control was compiled. Next, several classifiers were trained based on CNN to perform supervised classification using labels obtained from fluorescence microscopy images associated with each bright-field image. Model performances were evaluated and compared. The best model reached an AUC = 0.941 for classifying cells without treatment and AUC = 0.978 under drug treatment.

**F. Kanavati et al [4]** trained a CNN based on the EfcientNet-B3 architecture, using transfer learning and weakly-supervised learning, to predict carcinoma in WSIs using a dataset of 3,554. They obtained highly promising results for differentiating between lung carcinoma and non-neoplastic with high ROC-AUCs.

**S. Sladojevic et al [5]** is concerned with an approach for plant disease recognition, based on leaf image classification. The model is able to recognize 13 different types of plant diseases. The steps required for implementing this disease recognition model are described, starting from gathering images to create a database, assessed by agricultural experts. Caffe, a deep learning framework developed was used to perform training. The results achieved precision between 91% and 98%.

**J. Huixian et al [6]** is extracting plant leaf features and identify plant species. Firstly, plant leaf images are segmented, and then extract shape and texture features. 50 plant leaf databases are tested and compared with KNN, SOM and SVM. The leaves of 7 different plants were compared, and found that ginkgo leaves were easier to identify. The class label of the test set can be obtained by reconstructing the deep learning model.

**L. Chen et al [7]** focuses on the application of CNNs to image classification. They analyze (1) basic structure of artificial neural networks and the network layers of CNNs, (2) classic predecessor network models, (3) SOAT network, and (4) comparison of various image classification methods. They have also summarized the analysis and discuss the current trends.

**J. Liu et al [8]** provides a definition of plant diseases and pests detection problem, puts forward a comparison with traditional methods. This study outlines the research on plant diseases and pests detection based on deep learning from three aspects: classification, detection and segmentation. Additionally, advantages and disadvantages are summarized. Common datasets are introduced, and performance is compared. They discusses challenges in applications using deep learning. In addition, possible solutions and research ideas are proposed.

**M. Rana et al [9]** aims to present a review related to applications of ML and DL for the detection of multiple diseases. A detailed analysis from the journals and conferences was done. It provides an overview of different approaches based on ML and DL for classification of multiple diseases. Experiments are performed using MRI dataset. This study will assist the medical practitioners and researchers to choose an appropriate diagnosis technique.

**Md. M. Hasan et al [10]** aims to demonstrate the performance of ML algorithms in rice disease detection. They examined different techniques. Performance has been evaluated based on the feature extraction, clustering, segmentation, noise reduction, and level of accuracy. They also showcases various algorithms in terms of training methods, pre-processing with clustering and filtering, and testing. In addition, discuss several challenges.

**D. Hong et al [11]** rethink HS image classification from a sequential perspective with transformers, and propose a backbone network called SpectralFormer. It is capable of learning spectrally local sequence information from neighboring bands, yielding group-wise embeddings. To reduce the possibility of losing valuable information, they devise a cross-layer skip connection to convey memory to deep layers by learning to “soft” residuals. The SpectralFormer is flexible, which can be applicable to both pixel and patch-wise inputs. They evaluate the performance on three HS datasets, showing the superiority over classic transformers.

**E. Korot et al [12]** analyse the performance and feature set of six platforms, using four cross-sectional and en-face medical imaging datasets to create classification models. The platforms demonstrated uniformly higher classification performance with the optical coherence tomography modality.

**K. Shankar et al [13]** introduces a new HPTI-v4 model for the detection and classification of DR. The contrast level of the image will be improved by the use of CLAHE. Then, the segmentation of the image was done using a histogram-based model. The HPTI-v4 model is applied to extract the required features and perform classification by a MLP. A series of experiments take place on MESSIDOR Dataset to guarantee the goodness. The results exhibited the supremacy of the HPTI-v4 model.

**C. Kyrkou et al [14]** focuses on the efficient aerial image classification for emergency response/monitoring. A dedicated Aerial Image Database for Emergency Response applications is introduced, and an analysis of existing approaches is performed. This analysis a lightweight convolutional neural network architecture is proposed, referred to as EmergencyNet, based on atrous convolutions to process multi-resolution features and capable of running efficiently, achieving up to 20× higher performance with minimal memory.

**B. Taha et al [15]** presents a review of drone detection and classification using ML. Addressed technologies encompass radar, visual, acoustic, and radio-frequency sensing systems. The finding demonstrates that ML-based classification of drones seems to be promising with many contributions. A general requirement-driven specification for the problem of drone detection and classification is still missing as well as reference datasets which help in evaluating different solutions.

**Table 2 Review summary**

| Ref. | Application | Data used | ML Algorithm | Results |
|---|---|---|---|---|
| [3] | Breast cancer | JIMT-1 human breast cancer cells | convolutional neural networks (CNN) | AUC = 0.941 cells without treatment. AUC = 0.978 cells under drug treatment. |
| [4] | Lung cancer | WSIs using a dataset of 3,554 | CNN based on the EfcientNet-B3 architecture | high ROC-AUCs |
| [5] | Plant disease recognition | 13 different types of plant diseases | Caffe, a deep learning framework | precision between 91% and 98% |
| [6] | classify plant leafs | 50 plant leaf databases | KNN, SOM, SVM, Deep learning model | Shortest recognition time and the highest recognition rate. |
| [7] | Application of CNNs | - | CNNs and SOAT network | - |
| [8] | Plant diseases and pests identification | Common datasets are introduced | deep learning | possible solutions and research ideas are proposed |
| [9] | detection of multiple diseases | MRI dataset | ML and DL | reduced time and high accuracy |
| [10] | rice disease detection | different datasets | ML algorithms | discuss several challenges |
| [11] | Sequence learning using image | three HS datasets | SpectralFormer | superiority over classic transformers |
| [12] | analyse performance and feature of six platforms | four cross-sectional and en-face medical imaging datasets | optical coherence tomography modality | - |
| [13] | Diabetic retinopathy | MESSIDOR Dataset | HPTI-v4 | exhibited the supremacy of the HPTI-v4 model |
| [14] | access disaster-stricken areas | Aerial Image Database for Emergency applications | EmergencyNet | 20× higher performance |

| | | | | |
|---|---|---|---|---|
| [15] | drone detection and classification | - | - | - |
| [16] | drone classification method | data set is prepared for a three type of drone | three-channel CNN, GoogLeNet | improved the accuracy from 89.9% to 99.8% |
| [17] | Cancer image classification | slightly modified version of the PCam dataset | DenseNet | - |

**B. K. Kim et al [16]** propose a drone classification method for polarimetric radar, based on CNN and image processing. They propose an image structure for three-channel CNN. To reduce the size of data, an image processing method and structure are introduced. The data set is prepared for a three type of drone, with a polarimetric Ku-band FMCW radar system. A famous CNN structure, GoogLeNet, is used. The method improved the accuracy from 89.9% to 99.8%, compared with single polarized image.

**Z. Zhong et al [17]** propose a metastatic cancer image classification model based on DenseNet. They evaluate the approach to the slightly modified version of the PCam dataset. That packs the clinically-relevant task of metastasis detection into a straight-forward binary image classification task. The experiments indicated that model outperformed. They also conducted data augmentation and study relationship between Batches and loss.

## 2.3 REVIEW SUMMARY

In order to understand the applications of deep learning techniques, a total of 25 research articles have been downloaded from Google Scholar. Among most relevant articles has been identified, which are focused on deep learning. Additionally, these deep learning techniques are applied for Image classification task. After filtering the articles a total of 15 articles are listed in this paper. According to the review, the deep learning techniques can be applied on different applications such as cancer identification, drone detection, Arial image classification, plant disease detection, plant species detection.

In these applications different datasets are used according to the application area. In addition, the different deep learning architectures are used. According to the studied literature the deep learning approaches can be applied for: classification, segmentation, feature extraction and recognition. Therefore, the deep learning techniques can be utilized with the different kinds of data. Additionally, promising for preparing the new and innovative applications. These techniques are efficient as well as provides high accurate results. Therefore, in order to understand the working of the deep learning techniques for image classification task. This paper is proposing an experimental study with the convolutional neural networks. This section is providing the summary of conducted study. The next section is providing a detailed discussion about the experiments performed with the deep convolutional neural networks.

# 3. PROPOSED WORK

This section is providing a detail about the application development by using the deep learning architecture.

### 3.1 SYSTEM OVERVIEW

Images are one of the popular way of information storage. In a number of applications like medical science, smart farming, social media, disasters management and others, the use of images are frequently seen [18]. However, the image based applications are a classical domain of research and innovation. But, as compared to the traditional applications, the size of database is increased and also increasing with the time. Therefore, the traditional ML techniques of image based data classification become less effective and accurate. In this scenarios, for dealing with large amount of image the deep learning techniques are become popular. The deep learning concept is an advance technique of machine learning. That usage a dense neural network architecture. There are a number of deep learning architectures are available [19].

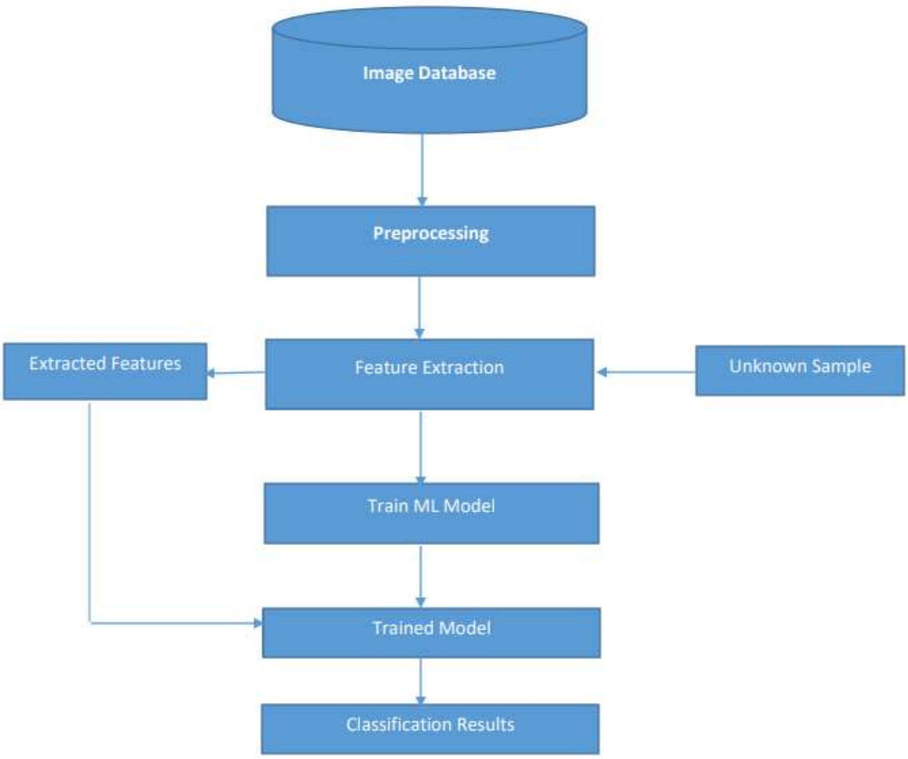


**Figure 1 Flow of the proposed model for image analysis**

The selection of deep learning architecture is depends upon the applications. For example, to learn with the different kinds of sequence and time based information, we can use the Recurrent Neural Network (RNN) and it's variant's like Long Short term Memory (LSTM). Additionally for dealing with the issues of image processing and relevant image data the Convolutional Neural Network (CNN) can be used. In this paper, the aim is to compare the performance of traditional machine learning approach of image classification with the deep learning based image classification. Additionally, experimentally verify the working of deep learning architecture utilizing in the real world applications. In this context, the problem of rice plant disease detection has been considered. Additionally, to develop the solution, the next section is providing the details of the required deep learning model.

### 3.2 EXPERIMENTAL MODEL

In this context, a system architecture is demonstrated in Figure 1. Using this experimental study, we are trying to demonstrate "how the image data is accepted using an application of ML or DL". Additionally, "how the data is being processed for identifying the target". In this context, the given diagram shows the different components. These components are:

**Image Database:** The ML based applications, initially requires the examples, by which the system can understand the target problem. In this presented work, the rice plant disease dataset has been used for experimental demonstration. This dataset is also known as Mendeley rice plant dataset. The dataset consist of four type of rice plant diseased images. The rice plant disease are 'Bacterial blight', 'Blast', 'Brown Spot' and 'Tungro'. It consists a total of 5932 RGB color images. This dataset consist images, which are from random angles and random zooming levels. Therefore, this dataset is containing the images as the real world captured images. Figure 2 shows the image samples from each type of diseases available in dataset.

**Pre-processing:** The aim of data pre-processing is to enhance the quality of learning data. The aim is to minimize the noise, improve the key features, enhance the size of data and manipulate data to reduce computational complexity of data processing. In this work the color image data has been used.

**(A) (B) (C) (D)**

**Figure 2 contains the rice plant disease images of (A) Bacterial blight (B) Blast (C) Brown spot and (D) Tungro**

Therefore, to reduce the computational cost of the machine learning algorithm, we normalized the images. The normalization is performed to scale the image pixel information between 0 and 1.

**Feature extraction:** In this work, the deep learning technique is used for the classification technique. In traditional techniques, the image features are extracted separately. Therefore, different feature extraction techniques are used. In this context, the Sobel edge detection, local binary patter (LBP) texture feature and color feature extraction techniques are used. On the other hand, in deep learning techniques the image features are extracted self. Therefore, three channel CNN can be an effective method for extracting and utilizing the extracted features self for learning. In addition, a two channel CNN is also configured for learning the features extracted by the traditional feature selection techniques namely the Sobel edge detection and local binary patter (LBP) .

**Train ML model:** There are a number of different kind of machine learning model. Additionally, the working of these models are depends on different parameters used. The machine learning algorithm is initialized using the selected parameters and then process the algorithm with data for preforming the training.

**Table 3 Model M1 two channel CNN Configuration**

| **Component** | **Details** |
|---|---|
| Model type | Sequential |
| Layer 1 | Conv2D, filters 32, kernel size 3 * 3, activation ReLu |
| Layer 2 | MaxPool2D, kernel size 2 * 2 |
| Layer 3 | Conv2D, filters 64, kernel size 3 * 3, activation ReLu |
| Layer 4 | MaxPool2D, kernel size 2 * 2 |
| Layer 5 | Flatten |
| Layer 6 | Dense, neurons 64, activation ReLu |
| Layer 7 | Dense, neurons 32, activation Sigmoid |
| Layer 8 | Dense, neurons 4, activation soft-max |

In this work, two configuration of convolutional neural network has been used for performing training. Here, first model is termed as M1, which is used with the traditional image features. Additionally, second model is denoted as M2, which network is a three channel convolutional neural network to learning with the image color frequencies. The configuration of model M1 is given in table 3 and second model M2 is given in table 4. Both the models are compiled with the ‘Adam’ optimizer and the loss function “categorical cross entropy” has been used. The implementation of both the models has been done using python technology.

**Table 4 Model M2 three channel CNN Configuration**

| **Component** | **Details** |
|---|---|
| Model type | Sequential |

| | |
|---|---|
| Layer 1 | Conv2D, filters 32, kernel size 3 * 3, activation ReLu |
| Layer 2 | MaxPool2D, kernel size 2 * 2 |
| Layer 3 | Conv2D, filters 64, kernel size 3 * 3, activation ReLu |
| Layer 4 | MaxPool2D, kernel size 2 * 2 |
| Layer 5 | Dropout, 50% |
| Layer 6 | Flatten |
| Layer 7 | Dense, neurons 360, activation ReLu |
| Layer 8 | Dense, neurons 180, activation ReLu |
| Layer 9 | Dense, neurons 128, activation ReLu |
| Layer 10 | Dense, neurons 4, activation soft-max |

**Trained model:** Both, the configured CNN models utilizing 80% training samples for performing the training the algorithms. The trained ML algorithm are now become capable to accept the new and unknown samples. The trained mode is performing classification to generate the class labels or identify the diseases of the plant leaf.

**Unknown Sample:** The trained algorithms are validated by using the remaining 20% of dataset samples. These samples are not used during the training therefore these samples are unknown for the trained CNN models. Basically, it is the simulation "how a user can perform a query to the system", for identifying type of disease in plant leaf.

**Classification results:** The trained ML algorithms, accept the unknown image samples and provide a disease name. By comparing predicted disease name and actual disease name the performance of the algorithms has been measured in terms of accuracy, loss. Precision, recall, and F-score. Additionally, the results are reported in the next section.

## 4. RESULT ANALYSIS

This section provides the discussion about the obtained performance for both the models i.e. bi-channel CNN and three channel CNN.

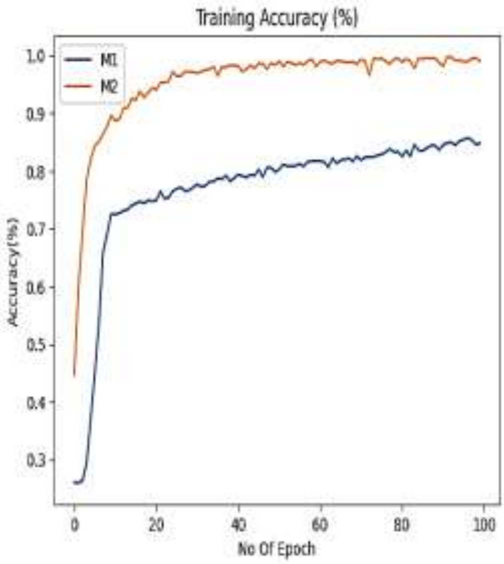


**Figure 3 Training Accuracy of Both CNN models**

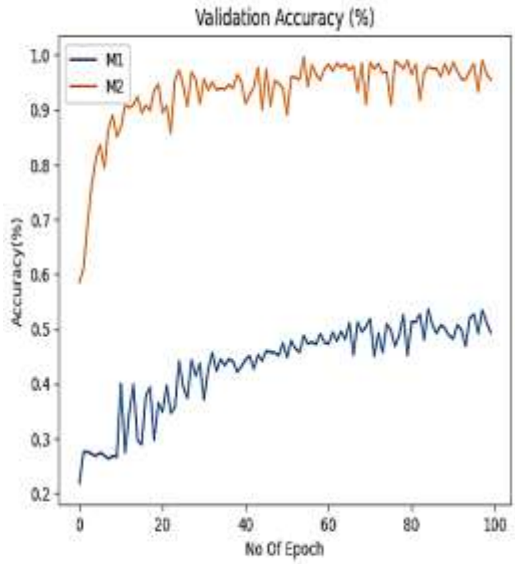


**Figure 4 Validation Accuracy of both CNN models**

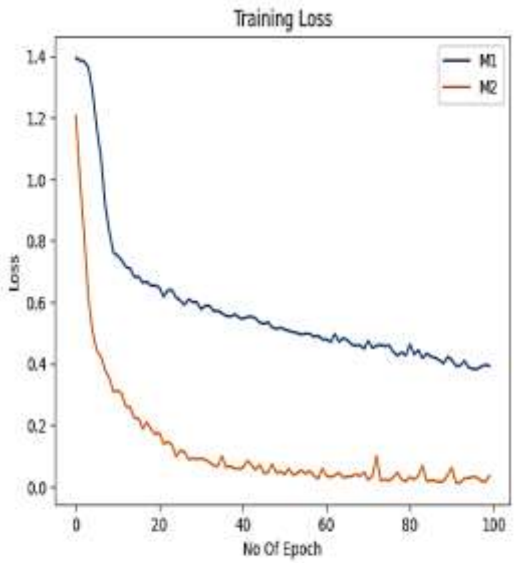


**Figure 5 Training Loss of CNN models**

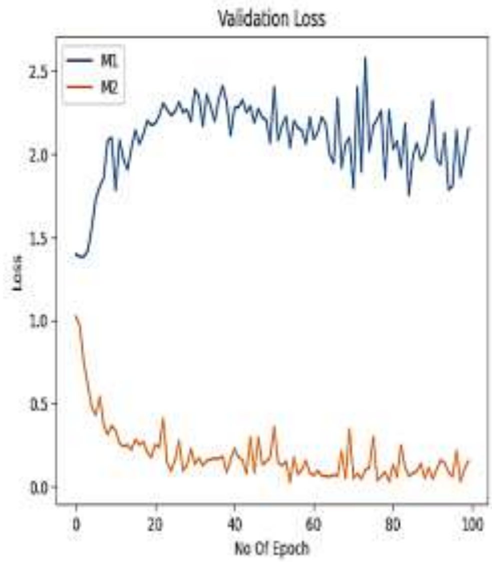


**Figure 6 Validation Loss of CNN models**

The bi-channel CNN is trained on the dataset features based on shape and texture feature. Additionally, the three channel CNN is trained on directly the dataset images. Basically in traditional techniques, the features are first extracted and then trained using the ML algorithm. Additionally, in deep learning the algorithm self-extract the image features from the color channels. The experiment has been done and for both training and validation has been performed. The results based on the conducted training and validation is given in figure 3 and figure 4 in terms of accuracy.

In both the diagrams, X axis shows the number of epoch or total training cycles. Additionally, in Y axis the accuracy in percentage (%) has been given. According to results given in figure 3, the Model M1 has low accuracy then model M2. But, using this figure we can see the training accuracy of both the models are enhancing with the increasing number of epoch. Similarly, in figure 4 the model M1 is performing very low as compared to model M2. On the other hand, when we trying to compare the training and validation performance, then we found a huge difference in their own performance. By using this comparison, we found there are 25% low performance is recorded during the validation of the model M1. On the other hand, when we comparing the model M1 with Model M2, then we found in both the cases i.e. training and validation the model M2 is providing accurate results. Additionally, there are very small difference in performance when we comparing the model M2 training and validation case. Similarly, the loss of both the models are also measured. The training loss of the models are given in figure 5 and for validation of the models the recorded loss is demonstrated in figure 6.

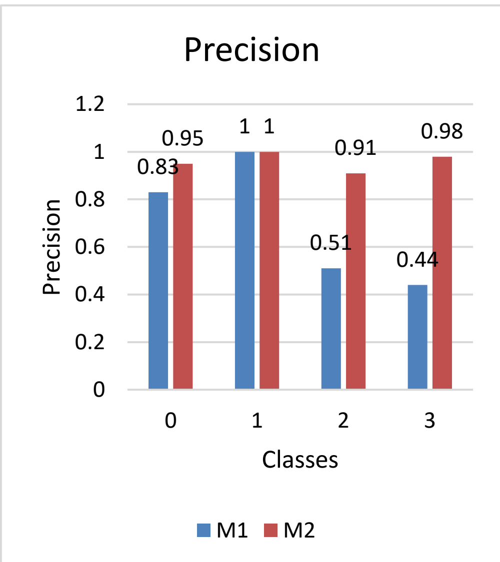


**Figure 7 Class wise precision of both models**

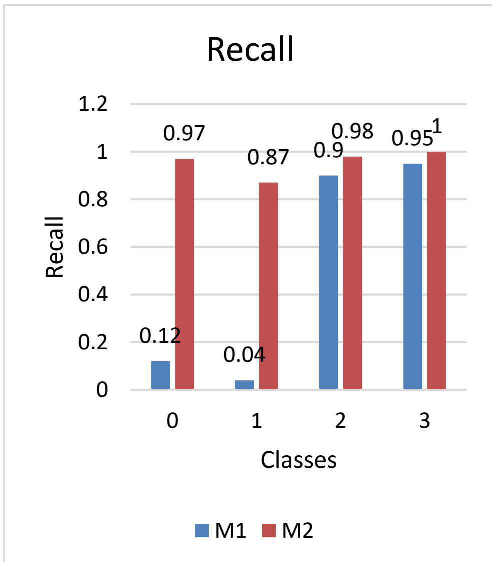


**Figure 8 Class wise recall of both CNN models**


**Figure 9 Class wise F-score of CNN models**

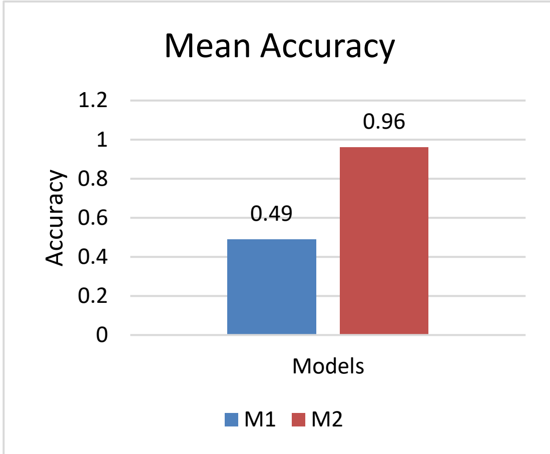


**Figure 10 Mean Accuracy of both the CNN algorithms**

In both figures, X axis shows the epoch and Y axis shows the loss of the models. Basically, the loss is not measured in percentage but measured as the difference between predicted and actual values. In a machine learning modeling, during training the ML models are trying to reduce the loss function. The loss is reduced by adjusting the weights of the neurons. According to the measured loss for training, we can see both the models are reducing the loss values. On the other, hand the validation loss of model M1 is increasing and validation loss of model M2 is reducing. Therefore, by using both the training and validation performance, we can say the model M2 is performing better than model M1.

After evaluation of the model the classification report of models are also calculated. Using the classification report, we can measure class wise precision, recall, f-score and mean accuracy. Precision is also known as positive predictive value. That is the fraction of relevant instances among the retrieved instances. Precision is defined as follows:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Where, TP indicates the True Positive, and FP shows the False Positive ratio

The precision of the models are given in figure 7, in this diagram X axis contains the classes or plant leaf diseases, and Y axis shows the precision score between 0 and 1. According to the obtained results in terms of class wise precision, we can say the model 2 is providing better classification accuracy for all the given classes. The precision is relevant to the accuracy of a model. Further, the recall of the models are also measured. Recall is also known as sensitivity or true positive rate and is defined as follows:

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Where, FN shows the False Negative ratio.

The recall is also an indicator of the accurate classification, figure 8 shows the class wise recall score for both the CNN model. The X axis of the figure shows the classes to predict and Y axis shows the recall of the classes. According to the results, the model M1 is not able to classify diseases of the class 0 and 1. On the other hand, the model M2 is able to classify all the classes more uniformly. Therefore, the model M2 is more suitable for classifying the diseases. Next, the f-score of the model is also calculated. F1-score is a metric which takes into account both precision and recall therefore that is a harmonic mean of precision and recall in order to describe the quality of classification outcomes. It is defined as:

$$\mathrm{F1-Score} = 2 * \frac{\mathrm{precision} * \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

The f-score is a decision parameter which is used to decide the classification accuracy. Figure 9 shows the class wise f-score of the algorithms. In this figure, X axis shows the classes to predict and Y axis shows the f-score between 0 and 1. According to the results, model M2 is providing superior performance than model M1. On the other hand the model M1 is not able to recognize all the given classes.

Additionally, the mean accuracy is also calculated using classification report. The accuracy is the ratio of correctly recognized information and total information produced for recognition. The accuracy can be measured using the following equation:

$$\mathrm{accuracy} = \frac{\mathrm{correctly\ recognized}}{\mathrm{total\ samples}}$$

The mean accuracy of both the CNN models i.e. bi-channel CNN and three channel CNN, are given in figure 10. In this diagram, X axis include the algorithms applied and Y axis shows the mean accuracy in terms of percentage. According to the given results, the model M1 is only capable to produce 49% accuracy classification results. Additionally, the model M2 is providing accuracy up to 96%. In addition, the training time of both the models are also calculated. The training time can be calculated using the following equation:

$$\mathrm{Training\ Time} = \mathrm{End\ Time} - \mathrm{Start\ Time}$$

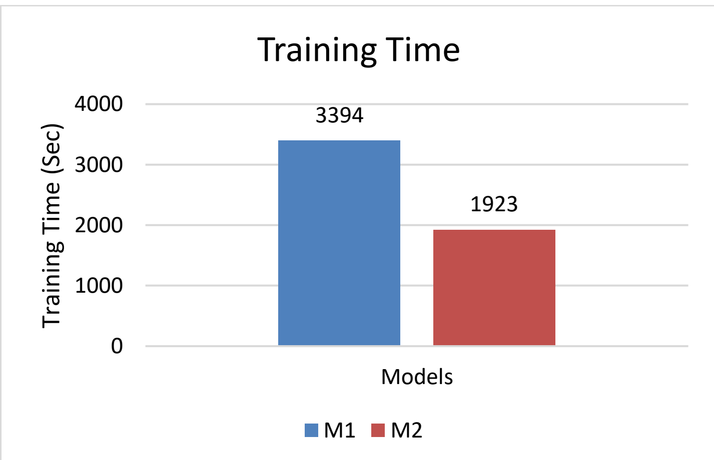


**Figure 11 Training time of the CNN algorithms**

The training time of both the deep learning models are demonstrated in figure 11. The time utilized is measured here in terms of seconds. In X axis of the diagram includes the trained model and Y axis shows the used time in seconds. According to the results, model M1 is consuming higher amount of time as compared to model M2. The Model M2 utilized 35% less time as compared to the model which is trained using two different kind of features.

## 6. CONCLUSIONS

The main of this paper is to discuss the image processing techniques and its applications. Therefore, first of all a review has been carried out based on recent research articles. In this review, we found that there are a number of applications where we can use the image data for making critical decisions. In different application like smart farming, Arial image analysis, drones, medical science, etc., we can use the image processing applications. However, the image databases are also increasing more significantly. In this context, traditional machine learning techniques are become less effective. Therefore, to deal with the large databases, we need the deep learning techniques for better accuracy. Further, we experimentally validated this fact. Therefore, two convolutional neural network has been configured, first CNN model is utilizing the features extracted by the sobel operator and local binary pattern (LBP).

Second model is directly utilizes the color images with the three channel CNN. Both the model are trained and validation has been done. By using the experiments, the performance in terms of the algorithms has been measured in terms of precision, recall, f-score and mean accuracy. Additionally, for finding the efficiency the training time of the algorithms has also been calculated. According to the results, we found the models which utilizes the traditional models for classifying the images are more expensive then deep learning techniques in terms of time. Additionally, the deep learning model is more accurate than traditional technique of image classification. Therefore, in future image analysis applications we recommend to utilize the deep learning models.

## REFERENCES

[1] S. Y. Chen, J. Q. Zhang, Y. Y. Zhao, P. L. Rosin, Y. K. Lai, L. Gao, “A review of image and video colorization: From analogies to deep learning”, Visual Informatics 6 (2022) 51–68

[2] DR. P. K. Patra, “Lecture Notes on Digital Image Processing”, College of Engineering and Technology, BHUBANESWAR

[3] G. Pattarone, L. Acion, M. Simian, R. Mertelsmann, M. Follo, Emmanuel Iarussi, “Learning deep features for dead and living breast cancer cell classification without staining”, Scientific Reports, 11, Article number: 10304 (2021)

[4] F. Kanavati, G. Toyokawa, S. Momosaki, M. Rambeau, Y. Kozuma, F. Shoji, K. Yamazaki, S. Takeo, O. Iizuka, M. Tsuneki, “Weakly-supervised learning for lung carcinoma classification using deep learning”, Scientific Reports volume 10, Article number: 9297 (2020)

[5] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, D. Stefanovic, “Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification”, Hindawi Publishing Corporation, Computational Intelligence and Neuroscience, Volume 2016, Article ID 3289801, 11 pages

[6] J. Huixian, “The Analysis of Plants Image Recognition Based on Deep Learning and Artificial Neural Network”, IEEE Access (Volume: 8), 2020

[7] L. Chen, S. Li, Q. Bai, J. Yang, S. Jiang, Y. Miao, “Review of Image Classification Algorithms Based on Convolutional Neural Networks”, Remote Sens. 2021, 13(22), 4712

[8] J. Liu, X. Wang, “Plant diseases and pests detection based on deep learning: a review”, Plant Methods (2021) 17:22

[9] M. Rana, M. Bhushan, “Machine learning and deep learning approach for medical image analysis: diagnosis to detection”, Multimedia Tools and Applications (2023) 82:26731–26769

[10] Md. M. Hasan, A. F. M. S. Uddin, M. R. Akhond, Md. J. Uddin, Md. A. Hossain, Md. A. Hossain, “Machine Learning and Image Processing Techniques for Rice Disease Detection: A Critical Analysis”, Int. J. Plant Biol. 2023, 14, 1190–1207.

[11] D. Hong, Z. Han, J. Yao, L. Gao, B. Zhang, A. Plaza, J. Chanussot, “SpectralFormer: Rethinking Hyperspectral Image Classification with Transformers”, IEEE Transactions on Geoscience and Remote Sensing, 2021

[12] E. Korot, Z. Guan, D. Ferraz, S. K. Wagner, G. Zhang, X. Liu, L. Faes, N. Pontikos, S. G. Finlayson, H. Khalid, G. Moraes, K. Balaskas, A. K. Denniston, P. A. Keane, “Code-free deep learning for multi-modality medical image classification”, Nature Machine IntellIgence, VOL 3, April 2021, 288–298

[13] K. Shankar, Y. Zhang, Y. Liu, L. Wu, C. H. Chen, “Hyper parameter Tuning Deep Learning for Diabetic Retinopathy Fundus Image Classification”, IEEE Access, VOLUME 8, 2020

[14] C. Kyrkou, T. Theocharides, “EmergencyNet: Efficient Aerial Image Classification for Drone-Based Emergency Monitoring Using Atrous Convolutional Feature Fusion”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, VOL. 13, 2020

[15] B. Taha, A. Shoufan, “Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research”, IEEE Access VOLUME 7, 2019

[16] B. K. Kim, H. S. Kang, S. Lee, S. O. Park, “Improved Drone Classification Using Polarimetric Merged-Doppler Images”, IEEE Geoscience and Remote Sensing Letters, 1545-598X © 2020 IEEE

[17] Z. Zhong, M. Zheng, H. Mai, J. Zhao, X. Liu, “Cancer image classification based on DenseNet model”, Journal of Physics: Conference Series 1651 (2020) 012143

[18] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, R. Kaliaperumal, “Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture”, Agriculture 2022, 12, 1745

[19] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. A. Dujaili, Y. Duan, O. A. Shamma, J. Santamaría, M. A. Fadhel, M. A. Amidie, L. Farhan, “Review of deep learning: concepts, CNN architectures, challenges, applications, future directions”, . J Big Data (2021) 8:53