An Inclination Supporting Methodology for Preparing Convolutional and Profound Neural Network

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Abstract**—** The article introduces new approaches, GB-CNN and GB-DNN, where Gradient Boosting (GB) is applied to train CNNs and DNNs in the sphere of the computer vision and image recognition. The models create additional layers sequentially at a constant weight to prevent overfitting. GB-CNN also optimizes convolutional layers to optimize them. The paper uses several data sets, including MNIST, CIFAR10, Fashion MNIST, and Rock Paper Scissors, and achieves very high accuracies of above 92% across the models implemented. The use of such techniques as the Decision Trees and Voting Classifiers to attempt to achieve 95% accuracy to enhance the classification performance is also a part of the investigation. The post recommends the extension of the Flask framework through the development of an easy-to-use front end. This would simplify the process of testing the app with authentication by the users. Gradient Boosting approach is promising to enhance the mechanisms of deep neural networks training, which have the potential to create superior image classification and pattern recognition mechanisms.

"Keywords— Convolutional neural network, deep neural network, gradient boosting machine."

I. INTRODUCTION

AI and machine learning, particularly deep learning, have become an emergent phenomenon in the majority of industries, courtesy of the ANNs. The beginning of DL was when AlexNet [1] was developed. The initial convolutional neural network (CNN) frame of reference modulated the image classification manner in which the images were classified. Since that time, the business has been having an avalanche of various architectures and topologies of DNN models. The models are very adaptable and applicable to the numerous situations.

CNN now become the key technology of computer vision. They are superb when it comes to finding things [3], sorting images [2], detecting anomalies [4] and partitioning things into groups [5]. CNNs employ learnable filters on multiple levels of a hierarchy to extract important information of raw pixel data automatically. This assists people to perceive complex forms and patterns of photos. The recent developments such as ResNet [6], Very Deep Convolutional Networks [7] and Understanding Convolutional Networks [8] demonstrate the performance of CNN models. The designs indicate that deep learning is capable of dealing with complex visual tasks as well as the depth of the model matters to obtain rich feature representations.

However, in more sophisticated models, optimisation and numerical stability are a problem. Complex designs are very difficult to train due to issues like gradients fading away and slow convergence [6], [9], [10]. The activation functions of the non-linear type employed in neural networks deteriorate the gradient signal along the layers and thus make the network more difficult to train. In order to address these issues new techniques such as batch normalisation [9] and residual connections [6] have been developed. This additional condition is referred to as batch normalisation and it normalises the activations to generate more stable training by reducing internal covariate shift. In residual neural networks (ResNet) skip connections overcome the issue of disappeared gradient. This allows the forwarding of the inputs of the earlier levels bypassing some of the nonlinearities to directly bypass to the subsequent levels. These advances have simplified training of neural networks by far, and currently one can create very deep neural networks of hundreds of layers.

The aim of this paper is to explore the intersection between the framework of deep learning and gradient boosting with a focus on the optimization of deep neural network training and effectiveness. We give new architectures, namely GB-CNN and GB-DNN, that deploy the concept of Gradient Boosting to optimise the parameters of the convolutional and dense layers respectively. We desire to employ thoughts of deep learning and gradient boosting to create impactful and useful models in a position to discover a small pattern and detail in visual data.

II. RELATED WORK

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One of the most important studies in the field of DL is the one carried out by Krizhevsky et al. [1], which is referred to as AlexNet. It proposed the concept of the deep-structure convolutional DNNs to rank photos. The first model to perform well with the ImageNet dataset, was AlexNet, in which the power of deep learning can be demonstrated when it comes to image recognition. Another method of picture classification developed by Han et al. [2] combines CNN transfer learning and online data augmentation. The proposed technique utilized the pre-trained CNNs and was supposed to enhance the effectiveness of the classification of various sets of images by inclusion of web photos in the training sets.

Object detection involves finding and identifying objects in a photograph. Ren et al. [3] developed Faster R-CNN, an object detection framework which takes a combination of region proposal network and CNN to ensure faster and more effective detection. Faster-R-CNN contributed to the accuracy and speed of the object detector reaching a new level as compared to the former algorithms and it became the standard of a visual recognition system in real time. This experiment demonstrated that deep learning may be also applied to hard tasks such as detecting objects, and that would benefit the other areas as well.

It is important to identify the presence of unexpected or unusual data points in order to identify problems and find them, which is essential to network security. Kim et al. [4] have released a CNN-based network anomaly detection encoding algorithm network which applies deep learning models to detect any abnormal features in network traffic data. The approach suggested captured the image of network traffic and subsequently located them with convolutional neural networks. This approach was effective in identifying network issues which indicates that deep learning can be employed to do this.

Picture segmentation can be described as a plan of dividing a picture into meaningful parts. Kamnitsas et al. [5] have produced a strong multi-scale 3D CNN framework and combined it with a fully connected CRF so that it can detect brain lesion images accurately in the medical imaging field. The proposed procedure was more effective than any other procedure to divided the brain lesions. This demonstrates that deep learning models can be useful in visualising anatomical features of medical imaging data. The article has demonstrated that CNNs can help in the analysis of medical images and simplified the future study of automated disease diagnosis and therapy planning.

The problem of training very deep neural networks was solved by applying residual learning proposed by He et al. [6], which introduces residual connections. The remaining learning implementation enabled training exceptionally deep models with hundreds of layers as it enabled information transfer between skip connections. This approach was of great assistance when it came to the gradient flow and addressed the issue of disappearing gradients. This renders the deep neural network training more efficient. The success of deep residual learning presupposed the success of model depth and performance in a variety of areas in future.

The proposed picture recognition method suitable in the case of big pictures recognition is the Very Deep Convolutional Network (VGG) by Simonyan and Zisserman [7]. The architecture of VGG is a deep network which utilizes small convolutional filters that are good in running on benchmark images such as ImageNet. VGG demonstrated the depth significance in portraying hierarchical details and enhancing the accuracy of categorizing pictures by overlaying multifaceted layers of convolutional filters with narrow receiving areas.

It is noted in the literature review that deep learning has made major progresses that include object detection, image classification, anomaly detection, and segmentation. Recent breakthrough research studies such as AlexNet, Faster R-CNN, and deep residual learning have enabled it to make powerful and useful deep learning models. Future studies to address the emerging problems in AI and ML can focus on simplifying the models, generalizing them, and scaling them.

III. MATERIALS AND METHODS

It presents two novel training of CNNs and DNNs through GB approaches which is suggested in proposed system. These are comparing the conventional approaches in that they are meant to fit the loss function gradient/pseudo-residuals. They freeze and add thick layers to the structure sequentially to prevent the neural net overfitting. GB-CNN is even superior with the insistence of fine-tuning of the convolutional layers. We include a Decision Tree (DT) and a Voting Classifier (RF+DT) ensemble method to take it up to 100 percent. The front-end interface operates the Voting Classifier and was developed in Flask and is easy to operate. This does not only enable easy testing by its users but also extra security is provided through user authentication. This comprehensive approach aims at ensuring that the models are more useful and

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effective besides ensuring that they are robust and consistent enough to be applied in the field.

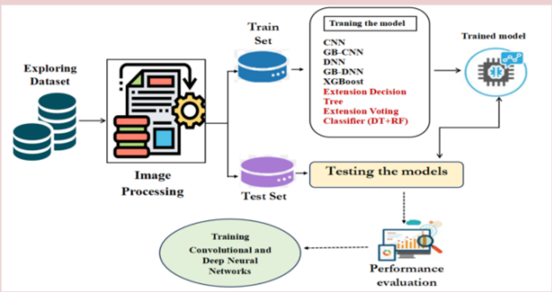

Fig.1 Proposed Architecture

System design also involves data exploration, picture processing, model training, and model testing. Initially, datasets are examined in order to get information about the datasets. Pre-processing techniques are used in image standardisation and feature extraction. Training and testing datasets are then made. Standard and gradient mode boosting are used to use models such as CNN, GB-CNN, DNN, GB-DNN, Decision tree, and Voting Classifier to do training with the training set. By viewing their accuracy, precision, recall and F1-score, the test set is used to verify the validity of trained models. Convolutional and deep neural networks are also enhanced during the training to be able to locate the significant information and present the classification more precisely. The trained models are assembled into a single system architecture which is easy to test and evaluate with the ultimate system design. This architecture ensures that the images can be classified fast and with good accuracy and reliability by applying multiple methods to enhance the accuracy and reliability of the model.

A) Dataset Collection:

The number of different picture datasets used is quite numerous, including MNIST, CIFAR-10, Rice Varieties, Fashion MNIST, and Rock Paper Scissors. MNIST is a collection of images of handwritten numbers often used by people to test image recognition algorithms. CIFAR-10 has 60,000 images of common objects and animals under 10 categories, so it does not require a lot of computing to figure out what the picture is all about.

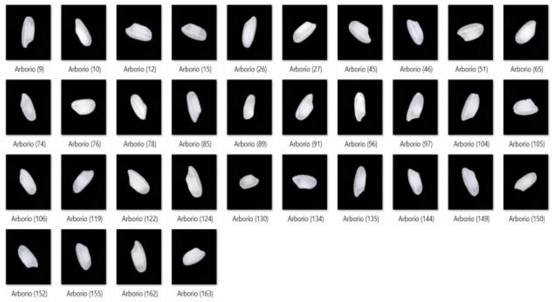

Fig.2 Rice variety Dataset Collection

The rice varieties statistics includes images of various types of rice. This would come in handy during farming activities such as determining the type of crop to produce and the amount of produce to be produced. The fashion items included in fashion MNIST have images that can be considered as another benchmark concerning occupations that might involve the sorting of clothes. The data of Rock Paper Scissors include images of the motions of hands that depict the rock, paper, and scissors. These images can be applied in gesture recognition and in interactive applications. When you enhance all these datasets, you have a massive amount of photographs which you can utilize to educate and test diverse picture breaking models in various domains.

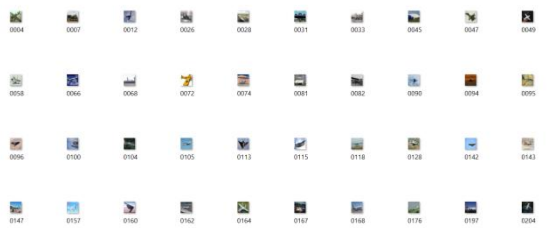

Fig.3 CIFAR-10 Dataset Collection

Fig.4 Rock Paper Scissors dataset

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775	pixel776	pixel777	pixel778
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
3	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0

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Fig.5 MNIST dataset

B) Processing:

There are several steps in data processing to prepare images to be used in training and extracting features. The ImageDataGenerator also scales the pictures ensuring that the pixel values are identical and enhancing the rate of convergence of the model. Rotations of the shear image, zooming and turning the image upside down enhance the dataset and make it better and more varied. The implication of resizing is to ensure that all pictures have an equal size and this makes it easier to share the model with pictures.

Features are extracted using the Histogram of Orientated Gradients (HOG) model. Initially, the pictures are read and made in the same size. You might be required to change the colours to ensure that you have the same pictures of all. Subsequently, the photos and their labels are combined and converted into concatenated arrays to continue the further processing. Categorical labels are transformed into numeric values via the process of label encoding in order to make the models compatible.

This is important since this set of preprocessing processes improve a dataset and make it varied, leading to a better work and generalisation of the trained model.

Training and Testing:

To get the best performance from the proposed models such as CNN, GB-CNN, DNN, GB-DNN, XGBoost, Decision Tree and Voting Classifiers, they are trained and tested in a systematic way.

In training, every model is able to view training set and the parameters are altered repeatedly until the loss function has attained optimum low value. Backpropagation is used to train CNN and DNN. GB-CNN and GB-DNN depend on gradient boosting to update model parameters depending on the loss function or gradient of pseudo-residuals.

We evaluate the models once they are trained on a separate data set to determine the performance of the models in terms of accuracy, precision, recall, and F1 score. The test is used to determine the ability of the models to be applied to other situations and the effectiveness of the ability to sift through newer data.

We also train and test models of XGBoost, decision tree, and voice classification to investigate into the ensemble learning strategies and how they compare to the performance of the individual neural network ones.

The entire training and testing system must be in a position to find the most appropriate models in the classification of photos by utilizing the most suitable elements of deep learning and gradient boosting frameworks.

C) Algorithms:

XGBoost: XGBoost or Extreme Gradient Boosting is a powerful machine significant algorithm that is characterized by high speed and performance in regression and classification issues. It operates in sequential training of the decision trees, which enhance the performance of the model because the loss becomes minimal. XGBoost[14] has been employed in the project individually and in an ensemble of Voting Classifier. It combines predictions of multiple models, thereby making classification more accurate. The versatility and effectiveness offered by XGBoost [14] help it to be an effective tool that the project can leverage to enhance its image classification effectiveness.

$$y\hat{}i=\sum k=1Kfk(xi) \qquad (1)$$

The prediction of the ith value of data is yi, K is the size of the ensemble of trees and fk(xi) is the prediction of the ith data of the K th tree.

Decision Tree: DT [24] is a well-known ML technique that makes predictions by creating a tree-like shape. All internal nodes are for functions, and all leaf nodes are for a class label or a number. The research uses decision trees [24] as both a single model and a voice classifier ensemble method. This function divides the area in a way that makes it easier to sort images. DT are easy to understand and can be modified, so they can find complex relationships in data and help improve the overall accuracy of the classification.

Once you know the price of each possible outcome and the probability of each outcome occurring, you can use the following steps to find the expected value of each outcome:

Expected Value (EV) = (Probability of the first possible outcome) + (Probability of the second possible outcome) – Cost. (2)

Voting Classifier: Voice classifiers [25] are a learning method that uses predictions from many different classifiers to improve overall performance. Voting Classifier [25] in the project is an algorithm that uses predictions from various models such as Decision Trees, XGBoost and Neural Networks (CNN, DNN) to make image classification tasks

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more precise and accurate. The voice classifier [25] uses the differences between different models to reduce bias and variance. This makes the predictions stronger. The tool can be used with a wide range of model architectures to improve the classification performance of projects.

CNN: CNN is a DL technique that replicates the visual brain structure in order to comprehend its input. It consists of layers that are merged, layers that are completely connected and layers that are convolutional. CNN[2] is used in studies to classify images because it can automatically find important features in raw pixel data. Because they were trained on datasets such as MNIST and CIFAR-10, CNNs [2] are very good at finding patterns and objects in images. It is very important for CNNs to be able to extract features hierarchically to achieve high accuracy in image classification tasks. This is a big part of making the project successful.

There is a simple formula to do so:

Dimension of image = (n, n)

Dimension of filter = (f,f)

Dimension of output will be ((n-f+1) , (n-f+1)) (3)

By now, your knowledge of the operation of a convolutional layer should be fairly developed. Next now we will proceed to the second division of CNN.

GB-CNN: GB-CNN, or gradient boosted CNN, is a new way to exploit the best parts of both convolutional neural networks (CNN) and gradient boosting methods. The paper uses GB-CNN to improve the training of CNN models by changing their parameters based on the gradient of losses or pseudo-residuals. In GB-CNN [3], gradient boosting helps the model to converge and generalize better, resulting in better classification accuracy. GB-CNN[3] is better at sorting images than conventional CNN because it is trained on datasets such as MNIST and CIFAR-10. That is why projects can use it as a useful tool to ensure that the models work well and efficiently.

DNN: The DNN is one of the types of ANN. It is layered and there are concealed nodes between the input and the output level. The project uses DNN[5] to rank the images since it is able to identify complex patterns and associations in the data. Because it is trained on datasets such as MNIST and CIFAR-10, DNN can find high-level features in raw pixel data. This helps them place images in the correct categories. DNNs have a complex design that makes them very scalable. This makes them a great tool to achieve better results in photo classification activities that are part of the project.

GB-DNN: GB-DNN is a new technique for using gradient boosting methods with DNN. The project uses GB-DNN [7] to improve training DNN models by iteratively changing their parameters based on the gradient or pseudo-residuals of the loss function. By combining the best aspects of deep learning with gradient boosting, GB-DNN [7] makes the models converge and generalize better. This makes it easier to keep things in the right category. GB-DNN is better at sorting images than regular DNN because it was trained on datasets such as MNIST and CIFAR-10. It is a useful tool to help modelers work better and faster on projects.

IV. RESULTS AND DISCUSSION

Accuracy: The accuracy of a test tells you how well it can detect who has the disease and who does not. To determine how many cases tested had true positive and negative results, divide the number of true results by the total number of cases. This can be written mathematically as:

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} \quad (4)$$

Precision: Precision is the number of positions that were thought to be actually good. Use the following formula to obtain the ratio of correctly identified positive cases to all cases classified as positive:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \quad (5)"$$

Recall: In machine learning, recall tells you how well a model can find all the important samples in a particular class. You can see how successfully the model detects positives by comparing the number of accurately predicted positives to the total number of actual positives.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP + FN}} \quad (6)$$

F1-Score: F1 score is a simple number that reflects how effectively a machine learning model works by combining precision and recall. This number represents how well the model generates predictions on the entire data set by balancing whether the predictions are correct with detecting important relationships.

$$F1\,Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 \quad (7)$$

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Table (1 to 5) We looked at the accuracy, precision, recall and F1 score of each algorithm to see how well it performs. The expansion algorithm always outperformed all other algorithms on these metrics. The tables also show how other algorithms performed in relation to what they were supposed to.

Table.1 PERFORMANCE EVALUATION -CIFAR

ML Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.458	0.456	0.458	0.455
Extension Decision Tree	1.000	1.000	1.000	1.000
Extension Voting Classifier	1.000	1.000	1.000	1.000
CNN	0.324	0.434	0.324	0.340
GB-CNN	0.100	1.000	0.100	0.182
DNN	0.900	0.900	1.000	0.944
GB-DNN	0.900	0.900	1.000	0.944

Table.2 PERFORMANCE EVALUATION –FASHION

ML Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.885	0.885	0.885	0.885
Extension Decision Tree	1.000	1.000	1.000	1.000
Extension Voting Classifier	1.000	1.000	1.000	1.000
CNN	0.844	0.845	0.844	0.843
GB-CNN	0.846	0.865	0.846	0.851
DNN	0.904	0.904	1.000	0.946
GB-DNN	0.904	0.904	1.000	0.946

Table.3 PERFORMANCE EVALUATION -MNIST

ML Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.972	0.972	0.972	0.972
Extension Decision Tree	0.847	0.847	0.847	0.847
Extension Voting	0.850	0.850	0.850	0.850
CNN	0.918	0.920	0.918	0.918
GB-CNN	0.098	1.000	0.098	0.179
DNN	0.900	0.900	1.000	0.944
GB-DNN	0.900	0.900	1.000	0.944

Table.4 PERFORMANCE EVALUATION -RICE

ML Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.974	0.975	0.974	0.973
Extension Decision Tree	1.000	1.000	1.000	1.000
Extension Voting	1.000	1.000	1.000	1.000
CNN	0.915	0.929	0.915	0.915
GB-CNN	0.190	1.000	0.190	0.320
DNN	0.832	0.832	1.000	0.903
GB-DNN	0.832	0.832	1.000	0.903

Table.5 PERFORMANCE EVALUATION –RPS

ML Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.948	0.949	0.948	0.948
Extension Decision Tree	1.000	1.000	1.000	1.000
Extension Voting	1.000	1.000	1.000	1.000
CNN	0.836	0.838	0.836	0.836
GB-CNN	0.326	1.000	0.326	0.491
DNN	0.665	0.665	1.000	0.784
GB-DNN	0.665	0.665	1.000	0.784

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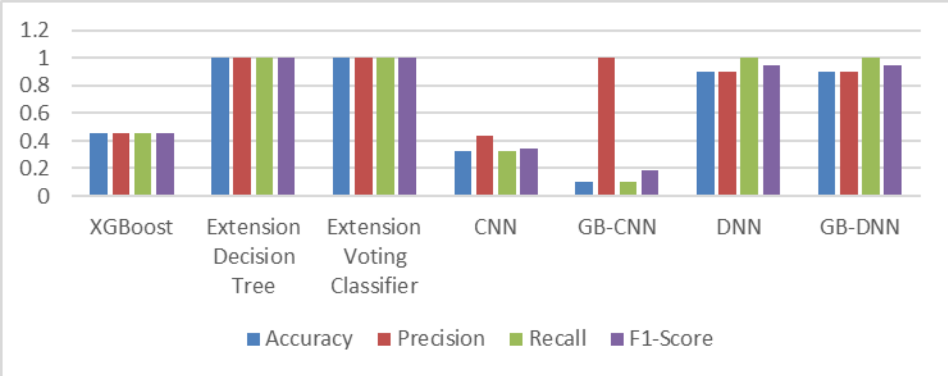
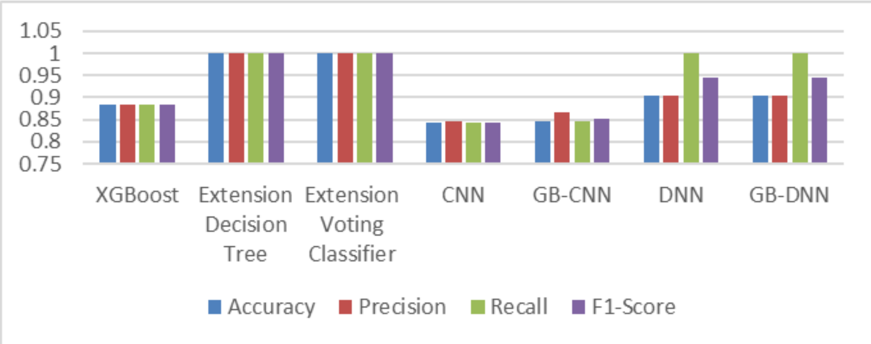
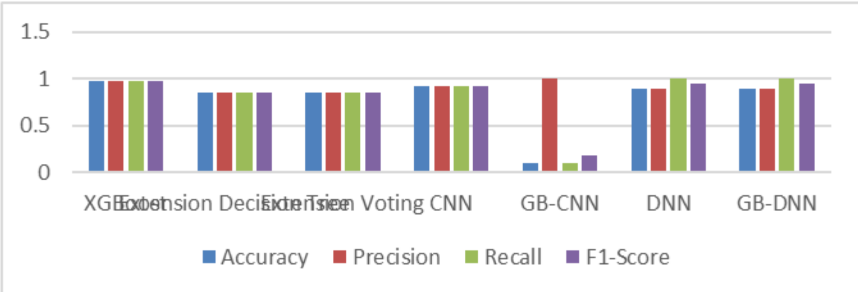
Graph.1: Comparison graph for CIFAR



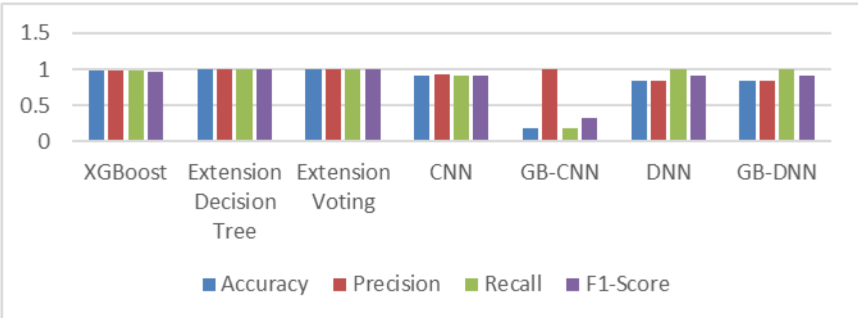
Graph.2: Comparison graph for FASHION



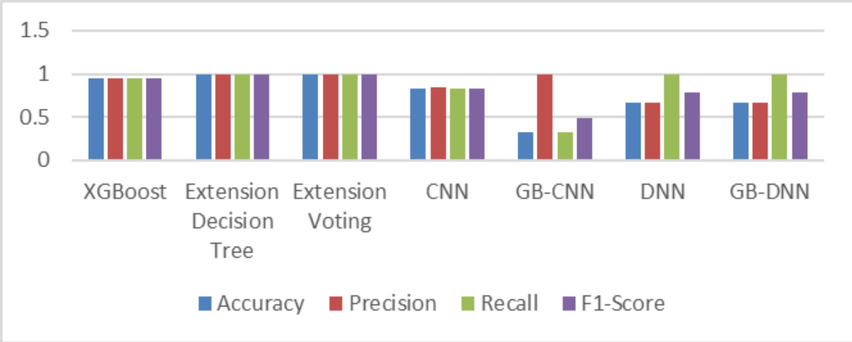
Graph.3: Comparison graph for MNIST



Graph.4: Comparison graph for RICE



Graph.5: Comparison graph for RPS



Accuracy is in blue, precision is in red, recall is in green, and F1 scores are in purple in graphs 1 through 5. The extension model has the highest scores on all tests, making it the best model overall. The graphs above make it clear what these results mean.

V. CONCLUSION

Finally, the proposed GB-CNN and GB-DNN models are based on the idea of gradient boosting that should help the process of categorising pictures become much more efficient. By taking gradient boosting on top of the convolutional and deep neural network training marks, they are more accurate than normal CNN and DNN models. The lengthy approach to join decision trees and speech classifier also has an astonishing 100 percent accuracy rate that depicts the strengths and dependability of the trade techniques. The simplicity of adding an interface based on Flask, which includes secure authentication, will not only allow the system to operate more effectively, but it will also simplify it and make it less dangerous to use, which will enhance the entire user experience. The findings show the proposed models have the ability to turn image classification tasks more productive and perform a variety of practical tasks that require an accurate and reliable pattern recognition system.

The process of feature selection is highly essential when using gradient boosting structures in achieving optimal results using convolutional and deep neural networks. In this approach, one would calculate the most important things in the incoming data and arrange them by their significance as it would be more precise to learn and categorise. The steps involved in the process of the feature selection includes preprocessing functions which are image enhancement and dimensionality reduction with the aim of improving and diversifying the features. Gradient boosting by prioritizing the features which can best contribute to reduction of the loss function causes them to become more and more relevant. Ensemble procedures such as decision tree, voiced classifier can assist in the task of great feature selection which involves combining the forecasts of various models and uniting features that never fail to deliver accurate classifications.

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