ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

Handwritten Digit Pattern Recognition by Hybrid of Convolutional Neural Network (CNN) and Bosting Classifiers

Arunima Banerjee[1]; Nitu Saha[2]; Washim Akram[3]; Saundarya Biswas[4]; Siddhartha Chatterjee[5]

[1,2]Dept. of CSE (IoT, CS, BT) University of Engineering and Management, Kolkata – 700160, West Bengal, India
[3]Department of Computer Science and Engineering, College of Engineering and Management Kolaghat, KTPP Township, Purba Medinipur – 721171, West Bengal, India
[4]Department of Basic Science and Humanities, College of Engineering and Management Kolaghat, KTPP Township, Purba Medinipur – 721171, West Bengal, India.
[5]Department of Computer Science and Engineering, College of Engineering and Management Kolaghat, KTPP Township, Purba Medinipur – 721171, West Bengal, India

Publication Date: 2025/07/17

Abstract— Patters are in many types like audio/video, character/digit etc. Pattern recognition refers to the task of identifying the pattern in an expert manner. Different researchers have applied different Machine Learning (ML) and Deep Neural Network (DNN) techniques for pattern recognition in different domains. This research is targeted to develop an expert system for hand written digit recognition. In this research a pattern recognition model is presented by using hybrid technique of Convolutional Neural Network (CNN) with three different boosting classifiers. The model is tested with handwritten digit data set downloaded from MNIST and EMNIST. The classification process initiated by applying CNN, used for features extraction and then three standard gradient boosting classification algorithms named Ada-Boosting classifier (ABC), Extreme Gradient Boosting classifier (XGB) and Light Gradient Boosting Machine (LGBM) is applied for classification. The experimental result shows that the integrated method of CNN and LGBM produce best accuracy of 99.51% and 99.7025% with MNIST and EMNIST dataset respectively.

Keywords: *Convolutional Neural Network (CNN), Ada-Boosting Classifier, XGBOOST Classifier, Light-GBM Classifier, MNIST and EMNIST Handwritten Digit Dataset.*

How to Cite: Arunima Banerjee; Nitu Saha; Washim Akram; Saundarya Biswas; Siddhartha Chatterjee; (2025) Handwritten Digit Pattern Recognition by Hybrid of Convolutional Neural Network (CNN) and Bosting Classifiers. *International Journal of Innovative Science and Research Technology*, 10(7), 1012-1025. https://doi.org/10.38124/ijisrt/25jul782

I. INTRODUCTION

The word "pattern" consists various types of the data's like : audio files, video files, image files, character file, digit files, voice or speech files, handwritten characters file, handwritten digits file etc.. Pattern recognition is the process to recognize the pattern in an efficient way. Handwritten digit pattern recognition is relatively very ingesting topic in the research domain. The task is challenging due to the availability of rich patterns of digits in the dataset. Handwritten digit recognition is not an optical recognition system and the task is harder because the digit writing patterns are different from person to person. This causes requires an expert system for digit pattern recognition. Machine Learning (ML) and Deep Neural Network (DNN) are most effective and advisable methods for solving respective problems.

Many of the researchers have performed their research work in the field of handwritten digit recognition with many of the datasets and they have achieved good recognition rate. Author [1-4] have used the application of traditional classification techniques like Dynamic Bayesian Network, Artificial Neural Network (ANN) etc. for prediction and recognition. As the same some of the author [5-8] used machine learning models and Convolutional neural network model like Support Vector Machine(SVM), K-Nearest Neighbors (KNN), Random Forest Classifier (RFC) and deep learning-based CNN classifiers for the handwritten digit recognition. Author [9] has proposed a robust classification model using CNN with 4 layers and compare with SVMand KNN with 99.1% of accuracy. Author [10-11] have used different gradient descent graphical processing based deep CNN for digit recognition with high accuracy. Some

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

authors[12-20] have proposed some integrated model for handwritten digit with the aim to earn better accuracy. Different Deep learning based DL4J model and integration of CNN and SVM is used for prediction. Author [21-24] have applied different Deep-CNN techniques and Evolutionary-DNN based model for the classification of handwritten digit recognition with maximum of 99.66% of accuracy.

The study of the literature inspired us to develop a hybrid model for classification and prediction of handwritten digit recognition. In this research a proposed hybrid model is proposed by combining deep learning networks with ensemble boosting classifier with the aim to earn higher accuracy. The hybrid model is developed by integrating Convolutional Neural Network with three different classifier named Ada Boosting classifier (ABC), XGBOOST classifier (XGB) and Light Gradient Boosting Machine (LGBM). In the proposed hybrid model named as CNN-ABC, CNN-XGB and CNN-LGBM, the CNN is applied for extracting feature and the other classifier applied for the classification [40,41,44].

II. PROPOSED ARCHITECURE

The architecture and workflow of proposed model is shown in figure 1.

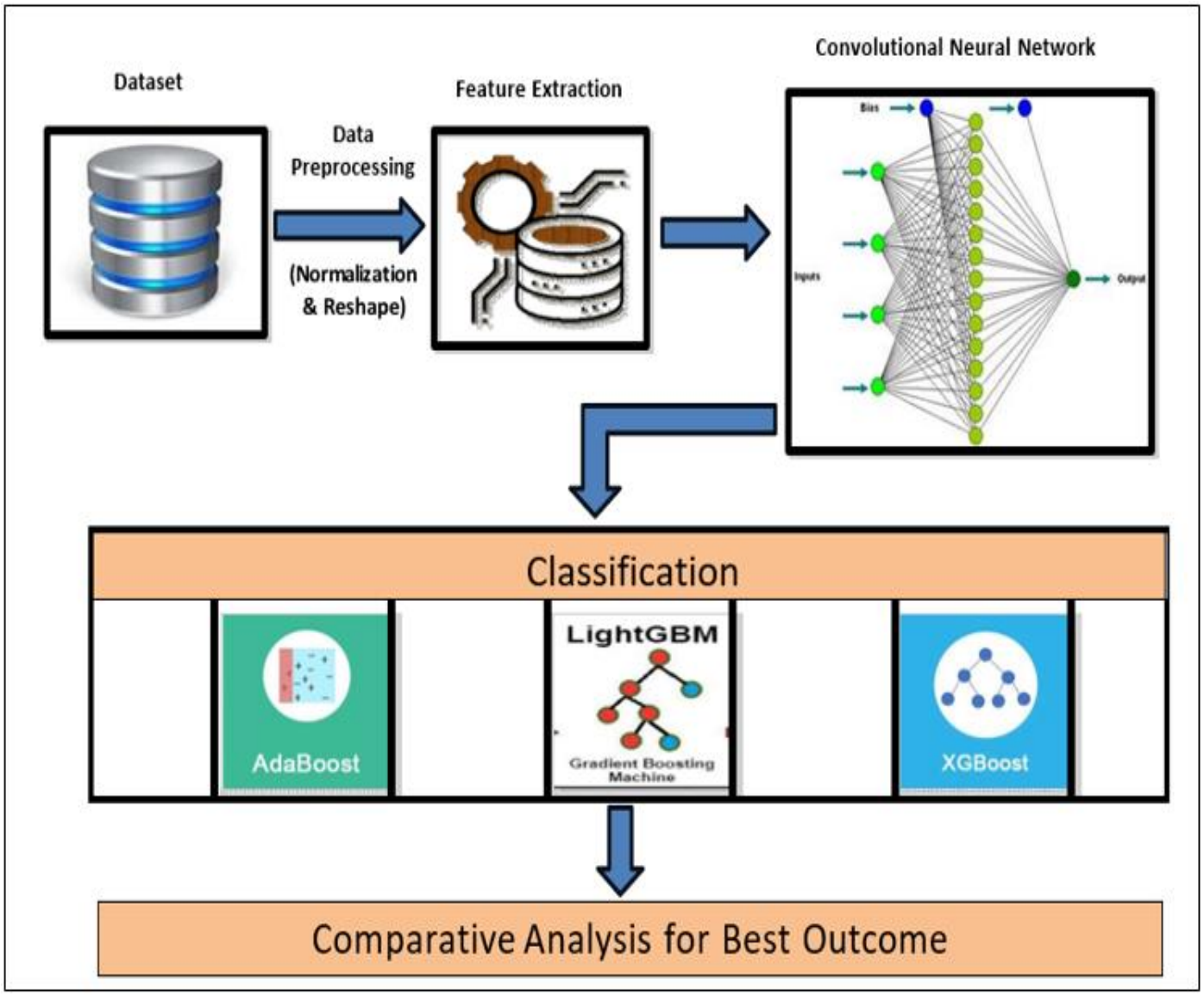

Fig 1 Flow diagram of proposed hybrid model

The proposed hybrid model is the combination of two major concepts, one is feature extraction and second is classification. The architecture of proposed model have 3 steps to completely classify the samples, where firstly we collect the images samples and nonmaize it, then perform the feature extraction by using CNN and then classify the extracted features of the samples by boosting techniques like : ABC, XGB classifier and LGBM classifier. Also we compare the recognition accuracy of the all three proposed model. The architecture of proposed hybrid model is represented below-

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

III. DATA SET

Handwritten digit dataset for recognition is collected from some of the well renowned data site. The data for the recognition will be image data that is downloaded and further used in hybrid model after preprocessing and reshaping.

IV. DATA PREPROCESSING

The preprocessing o includes the normalization and reshaping of data using predefined methods. The normalization includes the process of converting image to numerical values for calculation. In this process each pixel of the image is converted into 0 and 1. In addition reshaping of data is performed to enhance the image quality. Reshaping of data helps to improve the accuracy of recognition process.

V. FEATURE EXTRACTION:

Feature extraction is applied of extracting and enhancing the features from existing features. In this research work feature selection is aimed to advance the size of an image that will help to achieve to better accuracy rate while classification or prediction. In this research CNN has been used for extracting the feature of handwritten digit samples.

A. Convolutional Neural Network (CNN)

CNN is a basic architecture of deep learning era. When we perform the processing with multidimensional data like images and videos, it consumes less memory and time compare to an ANN. ANN is simply having one or two hidden layer, but CNN have multiple combination or multiple layers as hidden layer. CNN produce more and more refined result or accuracy for any type recognition compare to ANN results. Here Convolutional layer mainly used for feature extraction and dimensionality reduction. Convolutional neural networks also have multiple layers used to calculate the output for a given data set.

➢ *The standard architecture and properties of CNN*

- *The working structure of CNN has multiple layers:*

✓ Input layer (with preprocessing)
✓ Convolutional layer (with Activation function and Filters)
✓ Pooling layer
✓ Fully-connected layer
✓ Output layer

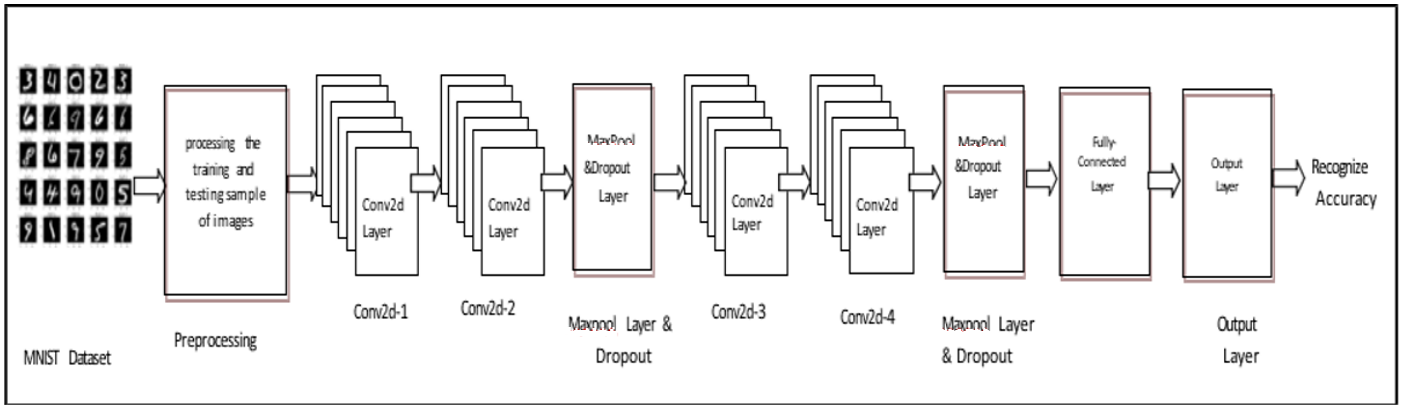

Fig 2 Convolutional Neural Network (CNN) Architecture

From Figure 2, from left to right, each block represents the successive layer of Convolutional neural network. This figure represents the input layer, some Convolutional layer with filter and activation function, followed by pooling layer with dropout. At the end the output layer of CNN is presented that produce the optimal result.

➢ Classification

Classification is the process where the data is partitioned into training and testing samples for classification process to develop an expert predictive system. The inputs for the classification are received after feature extraction process. For the classification we have applied three different bosting classifiers with the expectation of better accuracy. The different bosting classifiers are depicted below [42,43].

- *AdaBoosting Classifier (ABC):*

Ada-Boosting is the binary classifier, which gives good classification results. Ada-Boosting stands for adaptive boosting technique where strong classifiers are developed by integrating multiple weak classifiers for achieving good result. the working procedures of Ada-Boosting algorithm have some set of steps like: it first assigns the weight to all points of dataset, then gives it to the model and select the wrong classified points and then enhance the weight of that wrongly classified data points. These all steps are repeated till the end of data point of dataset. In each iteration, this model identifies wrong classified data points and increase in next step, so it takes more attention rather than previous iteration. That is the weakness of this algorithm.

- *XGBOOST Classifier (XGB):*

Extreme gradient boosting classifier is a supervised learning classifier largely used for object classification and regression. It can work with decision tree and can select the correct version of output. In this method all independent weighted variables are used to construct the decision tree for the prediction. The process will continue until the weight's assignments are correctly. These different classifiers/estimators are then combined to create a more robust and accurate model.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

- *Light Gradient Boosting Machine (LGBM):*

LGBM is an advancement of gradient boosting algorithm by appending some automatic feature selection techniques. it main y gives the attention to boosting patterns with large gradients. due to extra functionality of this model, it improves the accuracy and efficient of model. That are the main reason behind LGBM classifier is mostly used with tabular format data for classification and regression problem rather than standard machine learning models. Light GBM reduces the memory usage at the time of decision tree generation compare to XGB classifier.

➢ *Experimental Work*

The simulation of the proposed hybrid models are done using python software of version 3.7 available on anaconda navigator (anaconda3) with Tensor flow and Keras backup environment [27].Proposed Hybrid CNN-ABC, CNN- XGB and CNN-LGBM model is applied in handwritten digit samples collected from famous and genuine dataset repository known as National Institute of Standards and Technology (NIST).

➢ *Data Set*

In this research, we have used two famous dataset known as Modified National Institute of Standards and Technology (MNIST)and Extended Modified National Institute of Standards and Technology (EMNIST)[25-26] for simulation of our model. The description of dataset is explained below.

➢ *Mnist Dataset*

MNIST dataset is a popular repository for handwritten digits recognition. In this research the dataset is downloaded from http://yann.lecun.com/exdb/mnist/. The MNIST dataset is a collection of 70000 samples that is divided into four files, 1st for 60000 image sample used as training images, 2nd for 60000 labels of training samples, 3rd for 10000 image sample used as testing images and 4th for 10000 labels of testing samples. The MNIST dataset is represented in Figure 2that represents the total number of training and testing samples of digit 0- 9.

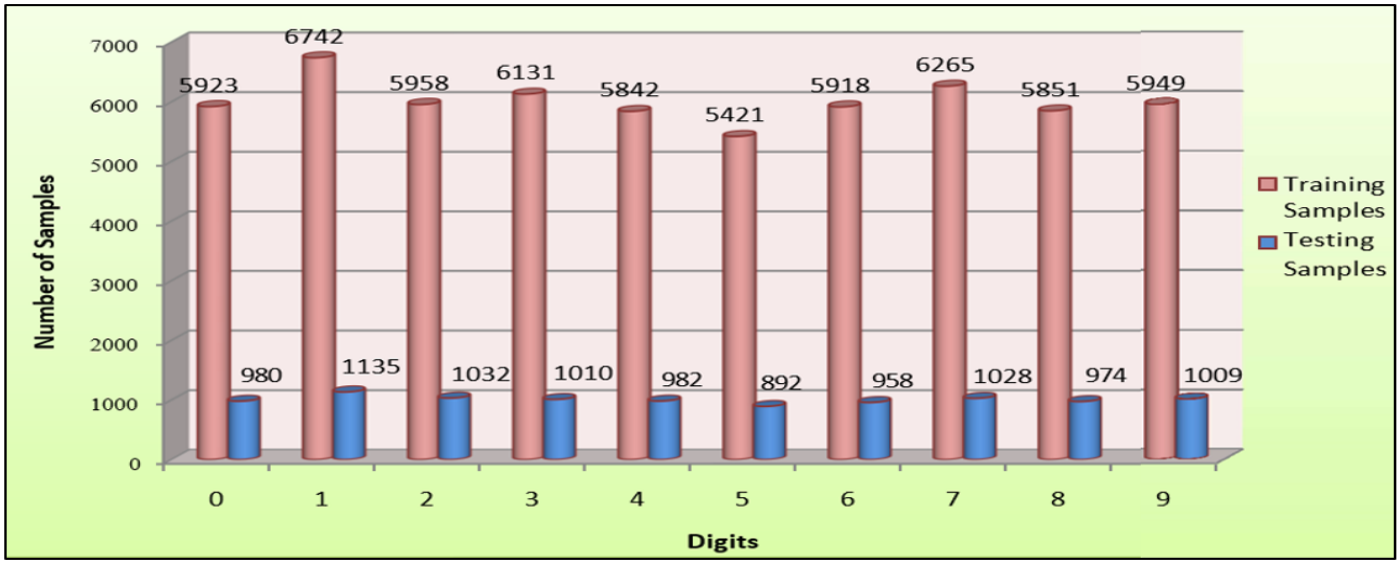

Fig 3 MNIST Training and testing samples of each digit (0-9) Convolutional Neural Network (CNN) Architecture

From the Figure 3, it is identified that there are the training samples 5923 and testing sample 980 available for digit zero, 6742 for training and 1135 testing samples for digit one and it is so on up to digit 9. The shape and dimension of the training and testing data is in the form of 28*28 matrixes. Some of the training dataset image samples presented in Figure 4.

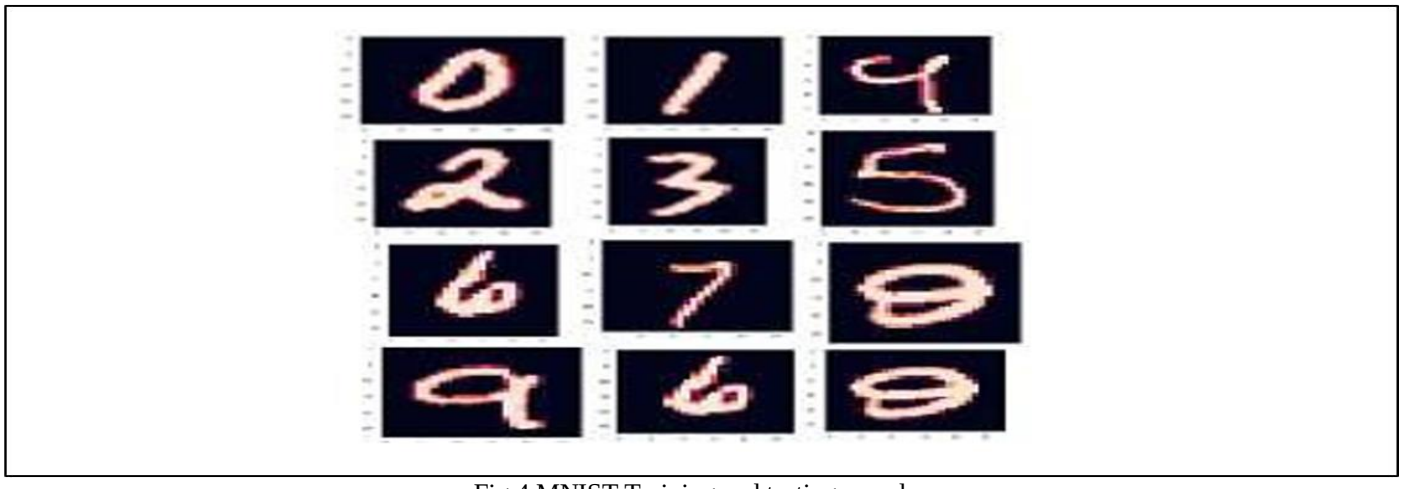

Fig 4 MNIST Training and testing samples

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

➢ *Emnist Dataset*

Another handwritten digit dataset known as EMNIST used for handwritten digit recognition. We have collected the EMNIST dataset from the website. https://www.itl.nist.gov/iaui/vip/cs_links/EMNIST/gzip.zip. In EMNIST dataset2,80,000 data samples are identified in which 2,40,000samples and 40,000 data samples are used for training and testing respectively. Total training and testing samples for digit 0 to 9 are represented in figure 5.

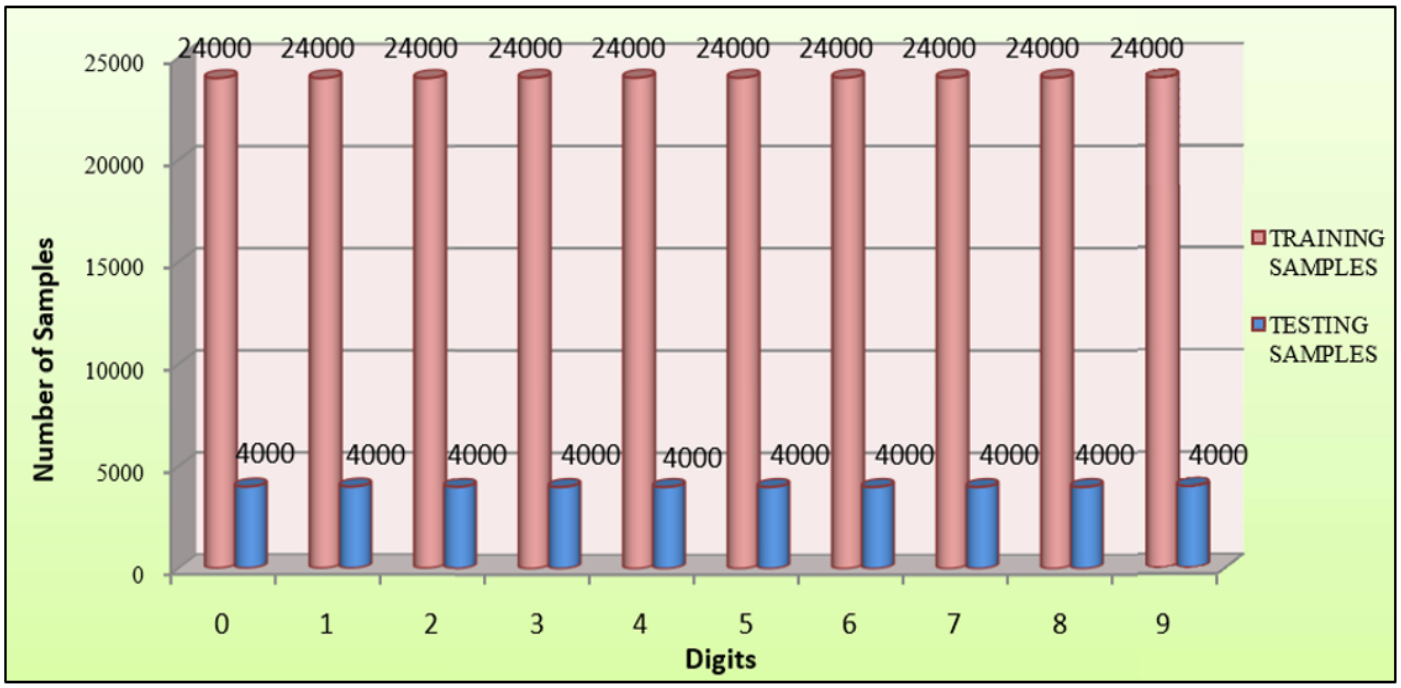

Fig 5 EMNIST Training and testing samples of each digit (0-9)

➢ *Data Preprocessing*

Initially the shape and dimension of the training and testing data of both MNIST and EMNIST dataset is in the form of 28*28 matrixes. The preprocessing of the dataset includes the process of normalizing and reshaping the data. After normalizing each image sample of training and testing dataset is converted into 0 to 1 presented in figure 6.

The next step of this experimental work is to reshape training and testing sample in 28*28*1 matrices presented in figure 6 [28]. After reshaping new image samples are used for further processing and model building.

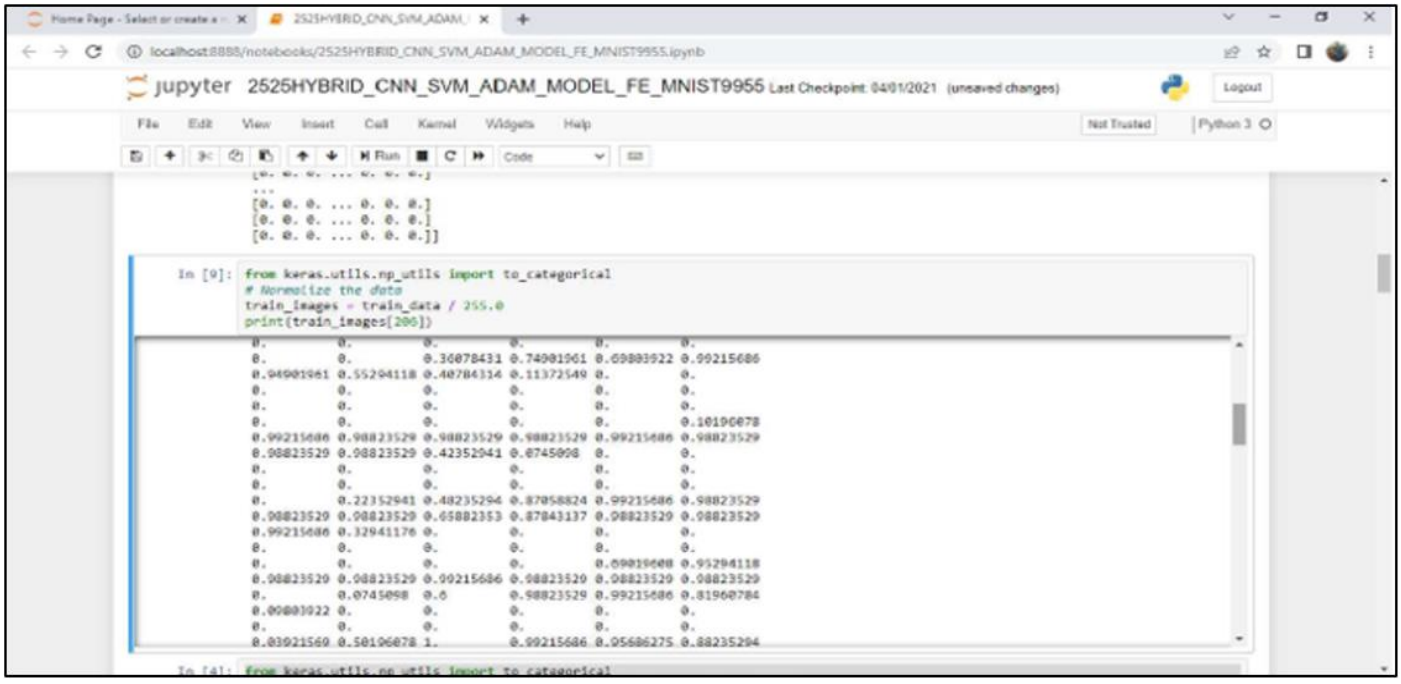

Fig 6 Snapshot of training sample after normalizing

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

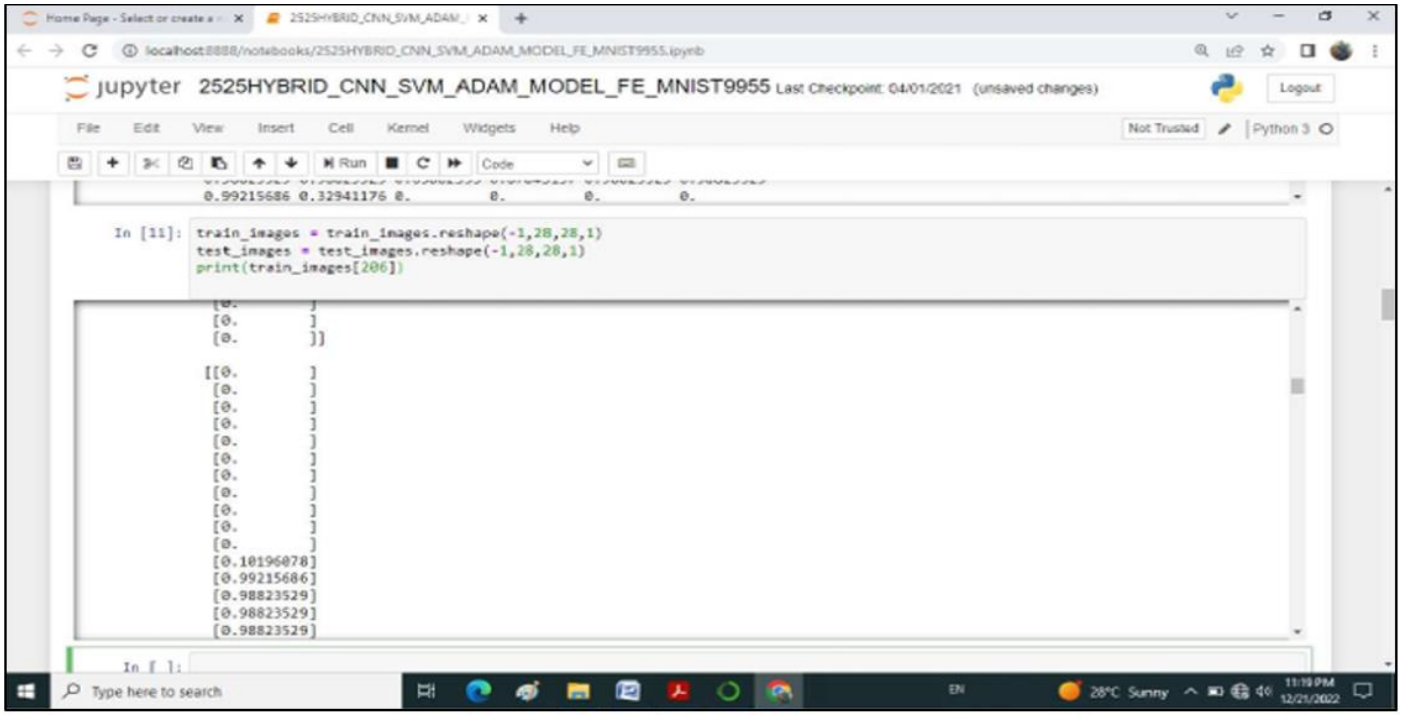

Fig 7 Snapshot of training sample after reshaping in 28*28*1 Matrices

➢ *Feature Extraction*

The feature extraction of pre-processed handwritten data is done using CNN. Feature extraction has performed by designing the custom CNN model with the pre-processed image samples. The custom CNN model with different parameters and layers highly useful and effective for feature extraction. The size of pre-processed image sample given to the custom CNN model is 28*28. The structure of custom CNN model contains 6 convolutional layer, 2 pooling layer with tuned parameters like kernel size, filters, batch normalization and stride. This process resizing the shape sample images for classification. After implementation of custom CNN model for feature extraction the outcome is the shape of each image is 3136 in size[29]. The outcome of the CNN implementation is presented in figure 8.

```
model.summary()
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_7 (Conv2D)            (None, 28, 28, 32)        832
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 28, 28, 32)        25632
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
batch_normalization_5 (Batch (None, 14, 14, 32)        128
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 14, 14, 32)        25632
_________________________________________________________________
batch_normalization_6 (Batch (None, 14, 14, 32)        128
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 14, 14, 64)        18496
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 14, 14, 64)        36928
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 7, 7, 64)          0
_________________________________________________________________
batch_normalization_7 (Batch (None, 7, 7, 64)          256
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 7, 7, 64)          36928
_________________________________________________________________
batch_normalization_8 (Batch (None, 7, 7, 64)          256
_________________________________________________________________
flatten_2 (Flatten)          (None, 3136)              0
=================================================================
Total params: 145,216
Trainable params: 144,832
Non-trainable params: 384
```

Fig 8 CNN architecture for feature extraction

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

➢ *Classification*

Classification of the handwritten digit dataset is done using three classifiers named ABC, XGB and LGBM. All these classifiers are implemented in python software with data received after feature extraction [30-32] [45]. The outcomes after classification using integrated models are explained below.

CNN-ABC: The estimator value for integrated model of CNN-ABC is set as 100,150,200 and 300. The testing accuracy after program evaluation is presented in Table1. Figure 9 and Figure 10 represents accuracy of testing and confusion matrix respectively obtained through CNN-ABC integrated model.

Table 1 Testing accuracy of the CNN-ABC model with MNIST and EMNIST

Number of Estimators	Recognition Accuracy of Testing Data	
	MNIST	EMNIST
100	**93.51%**	**94.55%**
150	92.00%	93.30%
200	90.36%	92.50%
300	90.35%	92.77%

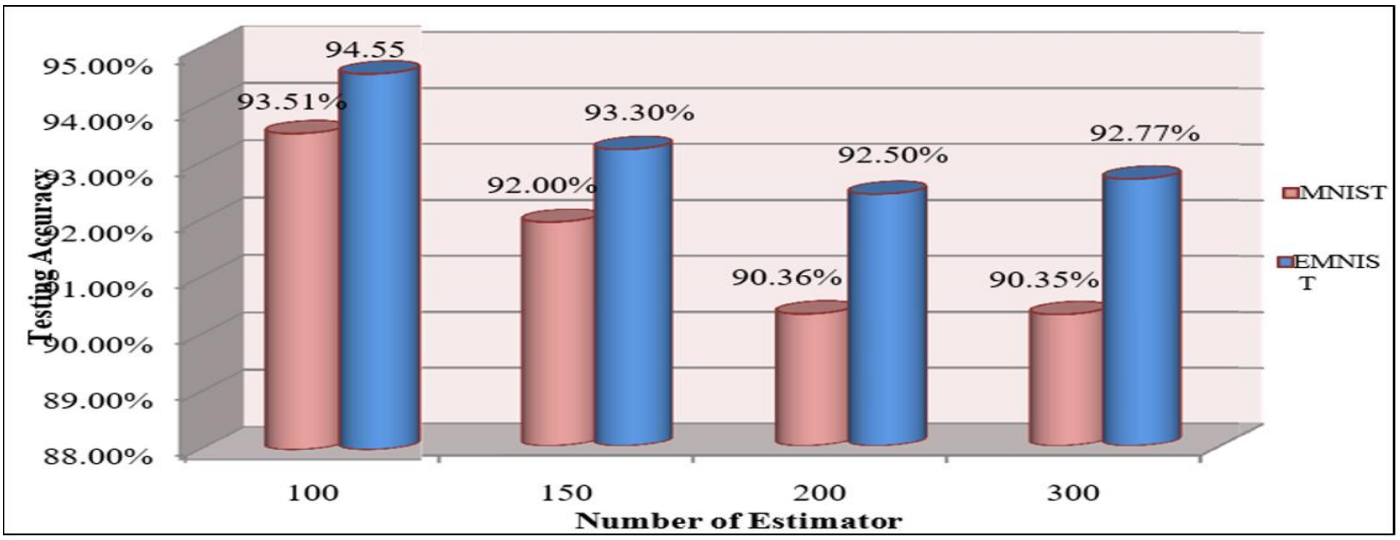

Fig 9 Testing accuracy of the CNN-ABC model with MNIST and EMNIST

➢ *CNN-ABC with MNIST*

```
Confusion Matrix:
[[ 905    0   15    0   17    9   16   12    6    0]
 [  13 1070    7    0   12    6   14   10    0    3]
 [   6    1  970    8    0   13    6   11    9    8]
 [   0    5    0  975    7    2    8    6    4    3]
 [   8    9   10   15  924    5    8    2    1    0]
 [  15    7    2    8    0  843    1    7    0    9]
 [  13   16    0    8    1    7  889   11   11    2]
 [  14   12   12    0   10    6    1  956    8    9]
 [  17    0   14   22    6   11    0   10  876   18]
 [  16   18    0   11   13    6    1    1    0  943]]
```

(A) CNN-ABC with MNIST

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

```
Confusion Matrix:
[[3810   17   28   26   17   22   31   12   16   21]
 [  25 3776   27   19   26   19   20   32   27   29]
 [  34   31 3741   38   18   33   22   29   17   37]
 [  16   15   35 3788   24   22   28   32   14   26]
 [  23   17   22   20 3779   30   34   15   24   36]
 [  12   10   19   12   19 3867   18   16   13   14]
 [  27   34   19   24   31   29 3752   15   39   30]
 [  30   17   37   32   22   40   16 3743   28   35]
 [  21   19   17   22   19   23   29   18 3811   21]
 [  25   34   26   22   36   31   27   19   27 3753]]
```

(B) CNN-ABC with EMNIST

Fig 10 Confusion matrix of CNN-ABC model

CNN-XGB: The estimator value for integrated model of CNN-XGB is set as 100,150,200 and 300. The testing accuracy after program evaluation is presented in Table2.Figure 11 and Figure 12 represents the accuracy of testing and confusion matrix obtained through CNN-XGB integrated model [33].

Table 2 Testing accuracy of the CNN- XGB model with MNIST and EMNIST

Number of Estimators	Recognition Accuracy of Testing Data	
	MNIST	EMNIST
100	**99.47%**	**99.51%**
150	99.39%	99.41%
200	99.39%	99.41%
300	99.39%	99.41%

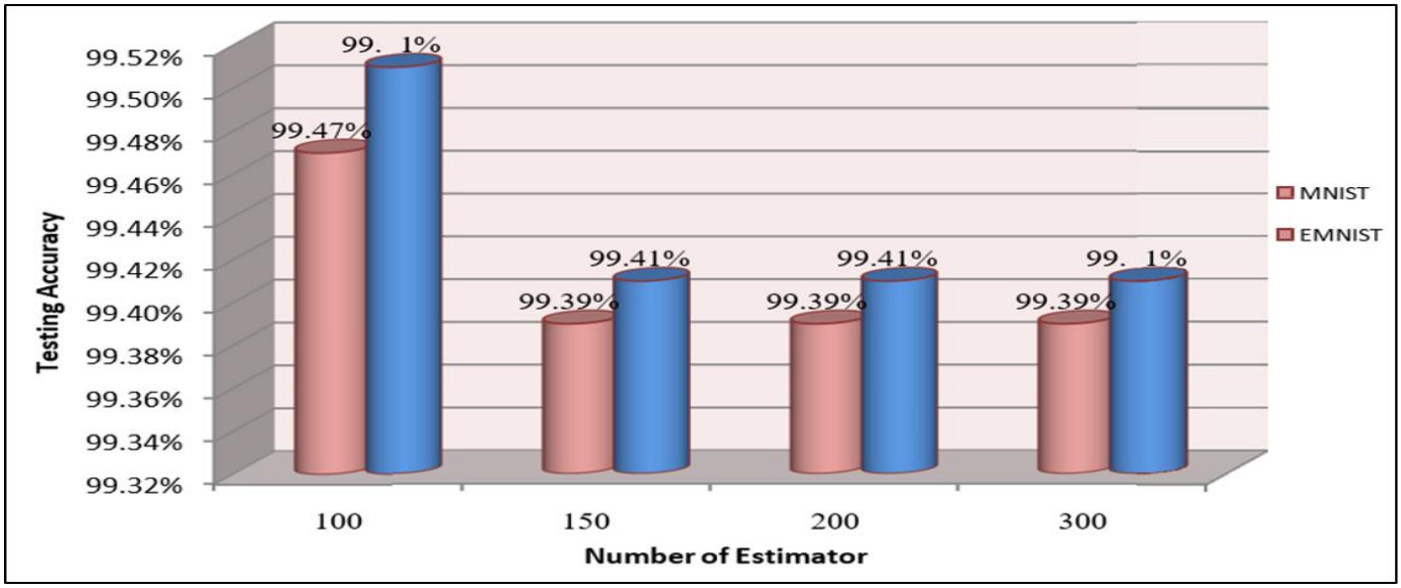

Fig 11 Testing accuracy of the CNN-XGB model with MNIST and EMNIST

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

```
Confusion Matrix:
 [[ 977    0    0    0    0    1    1    0    1    0]
 [   0 1133    0    1    0    1    0    0    0    0]
 [   0    1 1030    0    0    0    0    0    1    0]
 [   0    0    1 1004    0    3    0    1    1    0]
 [   0    0    0    0  977    0    1    0    0    4]
 [   0    0    0    3    0  888    1    0    0    0]
 [   1    3    0    0    1    1  951    0    1    0]
 [   0    2    3    0    1    0    0 1020    1    1]
 [   1    0    2    2    0    0    0    0  968    1]
 [   1    0    1    0    4    1    0    3    0  999]]
```

(C) CNN-XGB with MNIST

```
Confusion Matrix:
 [[3983    2    2    1    0    2    2    1    1    6]
 [   3 3981    2    0    1    1    0    6    2    4]
 [   0    2 3978    5    4    0    3    4    2    2]
 [   2    0    0 3989    0    6    2    1    0    0]
 [   1    5    4    0 3972    6    2    1    3    6]
 [   3    0    7    2    5 3976    3    0    4    0]
 [   1    2    1    0    0    2 3983    3    6    2]
 [   0    4    4    0    1    4    0 3982    0    5]
 [   5    3    2    3    1    1    5    0 3979    1]
 [   1    0    2    2    8    0    0    3    3 3981]]
```

(D) CNN-XGB with EMNIST

Fig 12 Confusion matrix of CNN-ABC model

CNN-LGBM: The estimator value for integrated model of CNN-LGBM is set as 100,150,200 and 300. The testing accuracy after program evaluation is presented in Table 3. Figure 13 and Figure 14 represents the accuracy of testing and confusion matrix obtained through CNN-LGBM integrated model [34-37].

Table 3 Testing accuracy of the CNN- LGBM model with MNIST and EMNIST

Number of Estimators	Recognition Accuracy of Testing Data	
	MNIST	EMNIST
100	**99.51%**	99.6625%
150	99.39%	99.6925%
200	99.41%	**99.7025%**
300	99.41%	99.7025%

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

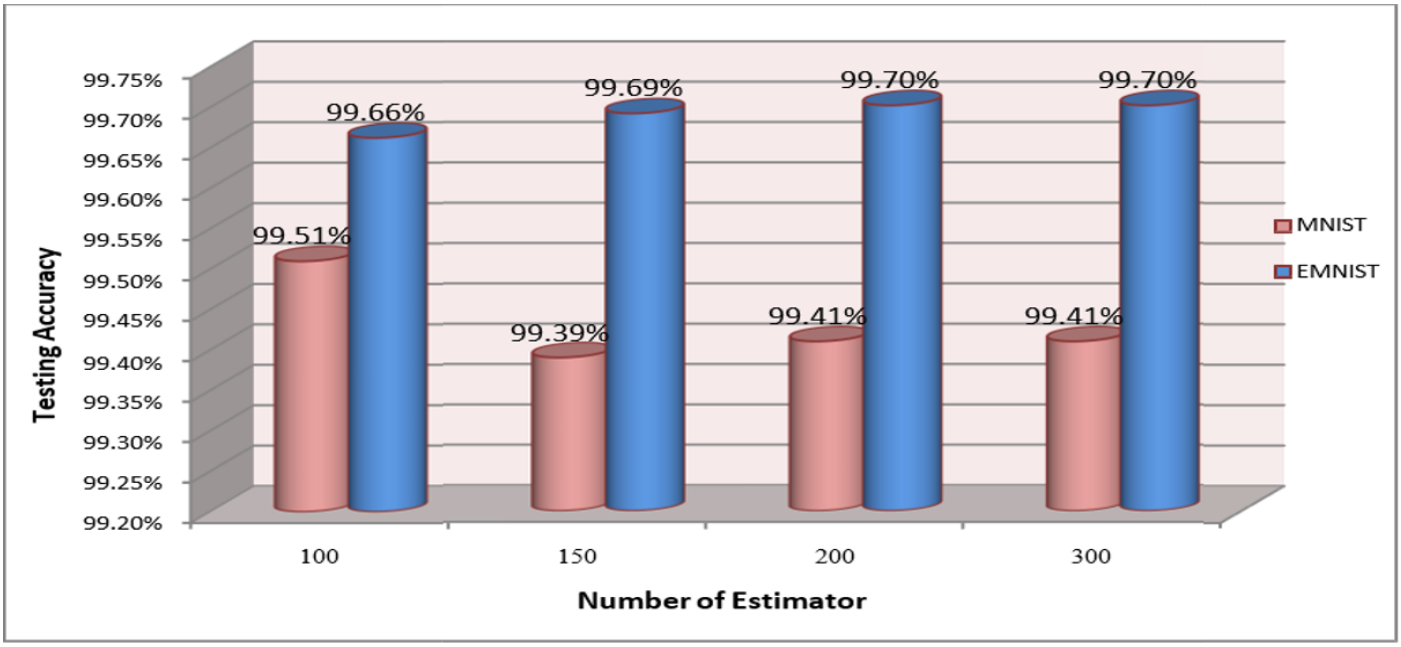

Fig 13 Testing accuracy of the CNN-LGBM model with MNIST and EMNIST

```
Confusion Matrix:
[[ 979    0    0    0    0    0    0    1    0    0]
 [   0 1131    1    2    0    0    0    1    0    0]
 [   0    1 1029    0    0    0    0    2    0    0]
 [   0    0    0 1007    0    1    0    1    1    0]
 [   0    0    0    0  977    0    1    0    0    4]
 [   0    0    0    2    1  887    2    0    0    0]
 [   3    3    0    1    1    0  949    0    1    0]
 [   0    3    1    0    0    0    0 1021    0    3]
 [   1    0    0    0    0    1    0    1  970    1]
 [   0    0    0    0    4    1    0    2    1 1001]]
```

(E) CNN-LGBM with MNIST

```
Confusion Matrix:
[[3987    2    1    0    0    1    4    0    3    2]
 [   0 3990    4    0    2    0    0    3    1    0]
 [   0    1 3985    6    1    1    0    2    3    1]
 [   0    0    4 3985    0    9    0    0    2    0]
 [   1    0    0    0 3983    0    2    3    1   10]
 [   0    0    0    7    0 3984    5    1    2    1]
 [   4    0    0    0    3    0 3992    0    1    0]
 [   0    1    2    2    3    1    0 3987    1    3]
 [   1    1    1    1    2    3    1    0 3985    5]
 [   0    0    0    1    5    1    0    4    2 3987]]
```

(F) CNN-LGBM with EMNIST

Fig 14 Confusion matrix of CNN-LGBM model

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

VI. COMPARATIVE ANALYSIS

The accuracies obtained through all three integrated techniques with different estimators are presented in table 4 and table 5 for MNIST and EMNIST dataset respectively. The comparative analysis of accuracies represents that the hybrid model of CNN-LGBM is the best classification model for both MNIST and EMNIST dataset with highest accuracy 99.51% and 99.7025% respectively. the comparative analysis is also represented graphically in figure 15 and figure 16.

Table 4 Testing accuracy of the proposed hybrid model with MNIST

Number of Estimators	Proposed Hybrid Models		
	CNN-ABC	CNN-XGB	CNN-LGBM
100	**93.51%**	**99.47%**	**99.51%**
150	92.00%	99.39%	99.39%
200	90.36%	99.39%	99.41%
300	90.35%	99.39%	99.41%

Table 5 Testing accuracy of the proposed hybrid model with EMNIST

Number of Estimators	Proposed Hybrid Models		
	CNN-ABC	CNN-XGB	CNN-LGBM
100	**94.55%**	**99.51%**	99.6625%
150	93.30%	99.41%	99.6925%
200	92.50%	99.41%	**99.7025%**
300	92.77%	99.41%	99.7025%

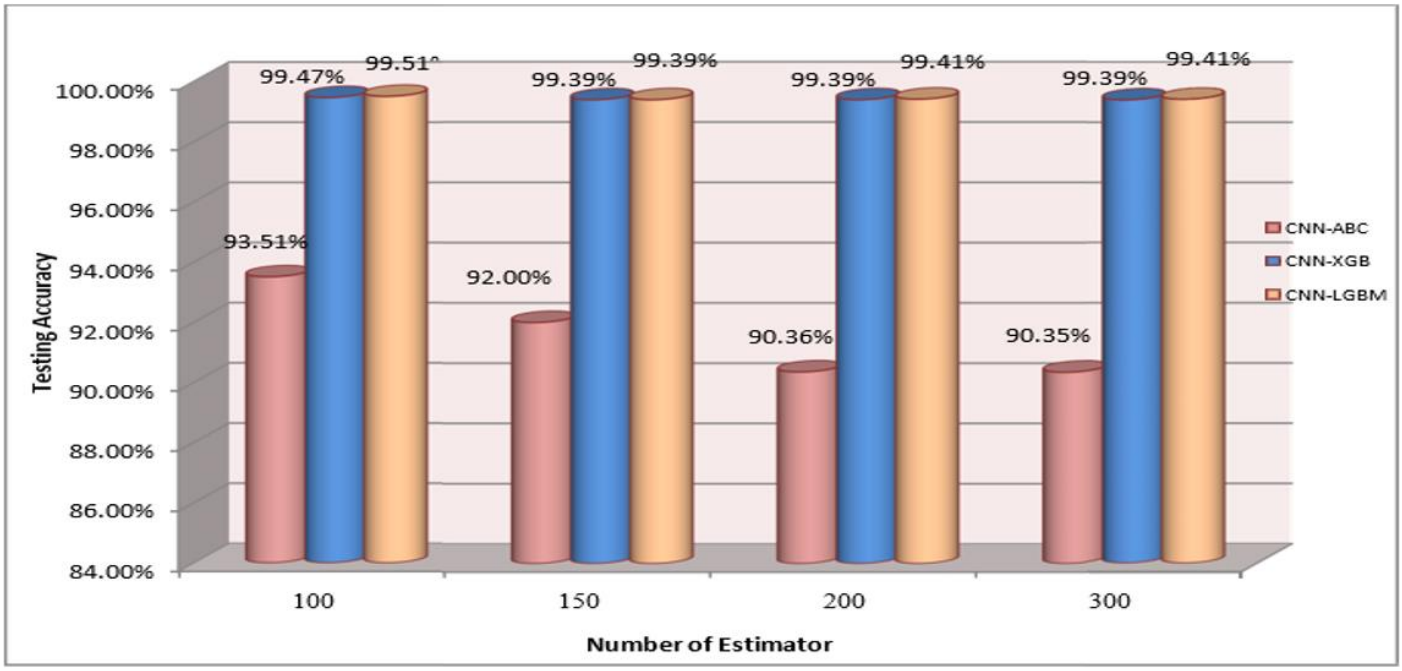

Fig 15 Testing accuracy of the proposed hybrid model with MNIST

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

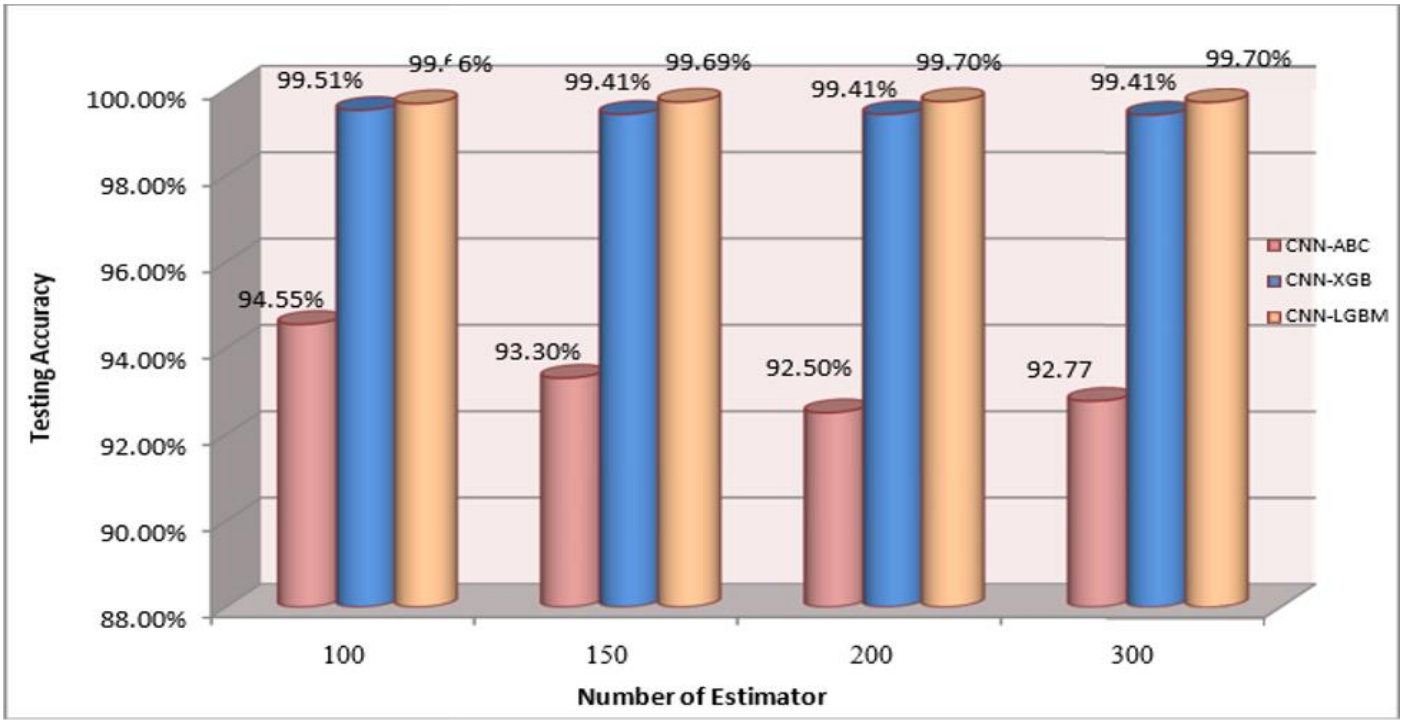

Fig 16 Testing accuracy of the proposed hybrid model with EMNIST

VII. CONCLUSION

In the area of pattern recognition, the handwritten pattern recognition domain are very much popular in between researches. In this paper we have also proposed CNN-ABC, CNN-XGB and CNN-LGBM based hybrid model for recognition of MNIST and EMNIST handwritten digit datasets. The hybrid model integrates the application of deep learning with gradient boosting approaches for best classification outcomes. In this proposed model the handwritten digit recognition process is initiated by applying custom CNN technique for feature extraction and then gradient boosting classifiers are applied for classification. In the experimental analysis we have identified that the best accuracy of 99.51% and 99.7025% is achieved in classification for MNIST and EMNIST data by using CNN-LGBM hybrid model.

REFERENCES

[1]. G. Vamvakas, B. Gatos and S. J. Perantonis, “Handwritten character recognition through two-stage foreground sub-sampling,” Pattern Recognition, vol. 43, pp. 2807-2816, 2010.

[2]. O. Pauplin and J. Jiang, “DBN-based structural learning and optimization for automated handwritten character recognition,” Pattern Recognition Letters , vol. 33, pp. 685-692, 2012.

[3]. V. N. Jagtap., S. K. Mishra, “Fast Efficient Artificial Neural Network for Handwritten Digit Recognition,” International Journal of Computer Science and Information Technologies, vol. 5, pp. 2302-2306, 2014.

[4]. M. Y. W. Teow, “Understanding Convolutional Neural Networks Using A Minimal Model for Handwritten Digit Recognition,” IEEE 2nd International Conference on Automatic Control and Intelligent Systems (I2CACIS), pp. 167-172, 2017.

[5]. A. Dutt and A. Dutt , “Handwritten Digit Recognition Using Deep Learning,” International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), vol. 6, pp. 990-997, 2017.

[6]. N. Jain, K. Rahul, I. Khamaru, A. K. Jha and A. Ghosh, “Hand Written Digit Recognition using Convolutional Neural Network (CNN),” International Journal of Innovations & Advancement in Computer Science IJIACS, vol. 6, pp. 260-266, 2017.

[7]. M. Zohra and D. R. Rao, “A Comprehensive Data Analysis on Handwritten Digit Recognition using Machine Learning Approach,” International Journal of Innovative Technology and Exploring Engineering (IJITEE), vol. 8, pp. 1449-1453, 2019.

[8]. N Sagar., Rajalekshmi J., U. Nikhil. S. , L . Dhrithi ., R. Tushar .B. ,(2019), Comparison Of Machine Learning Techniques for Hand Written Digit Recognition, International Research Journal of Engineering and Technology (IRJET) , 06, 05, 4972-4977

[9]. Agrawal A. K.,. Shrivas A. K., ,Awasthi V. K. (2021), A Robust Model for Handwritten Digit Recognition using Machine and Deep Learning Technique, 2021 2nd International Conference for Emerging Technology (INCET), 2021, pp. 1-4, doi: 10.1109/INCET51464.2021.9456118.

[10]. F. Chen, N. Chen, H. Mao and H. Hu, “Assessing Four Neural Networks on Handwritten Digit Recognition Dataset (MNIST),” Chuangxinban Journal Of Computing, pp. 1-4, 2018.

[11]. S. Mishra, D. Malathi, K. Senthilkumar, “Digit Recognition Using Deep Learning,” International Journal of Pure and Applied Mathematics, vol. 118, pp. 295-302, 2018.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

[12]. Ali Saqib, Shaukat Zeeshan, Azeem Muhammad , Sakhawat Zareen , Mahmood Tariq, ur Rehman Khalil (2019), An efficient and improved scheme for handwritten digit recognition based on convolutional neural network, Springer Nature Switzerland AG 2019

[13]. Dixit Ritik, Kushwah Rishika, Pashine Samay(2020), Handwritten Digit Recognition using Machine and Deep Learning Algorithms , International Journal of Computer Applications (0975 – 8887), 176 , 42,27-33

[14]. Agrawal A. K.,Hota H. S. ,Awasthi V. K. (2020), MNIST handwritten digit recognition using deep neural network technique: keras, Review of Business and Technology Research, 17(2), pp – 13-19, ISSN: 1941-9406 (Print), 1941-9414 (CD)

[15]. Agrawal A. K.,. Awasthi V. K. (2021), Novel Deep Neural Network Model for Handwritten Digit Classification and Recognition, International Journal of Advanced Research in Science, Communication and Technology (IJARSCT),2(2),30-35.

[16]. Niu Xiao-Xiao, Suen Ching Y. (2012), A novel hybrid CNN–SVM classifier for recognizing handwritten digits, Pattern Recognition 45, 1318–1325

[17]. Ahlawat Savita , Choudhary Amit(2019), Hybrid CNN-SVM Classifier for Handwritten Digit Recognition , International Conference on Computational Intelligence and Data Science (ICCIDS 2019) , Procedia Computer Science 167, 2554–2560

[18]. A. Agrawal, A. Shrivas, and V. Awasthi, “An Improved and Customized Hybrid of Deep and Machine Learning Technique Model for Handwritten Digit Recognition”, A Journal of Physical Sciences, Engineering and Technology (2022), vol. 14, no. 01 SPL, pp. 13-19, Jun. 2022.

[19]. Ren, X., Guo, H., Li, S., Wang, S., Li, J. (2017). A Novel Image Classification Method with CNN-XGBoost Model. In: Kraetzer, C., Shi, YQ., Dittmann, J., Kim, H. (eds) Digital Forensics and Watermarking. IWDW 2017. Lecture Notes in Computer Science(), vol 10431. Springer, Cham. https://doi.org/10.1007/978-3-319-64185-0_28

[20]. A. Taherkhani, G. Cosma and T.M. McGinnity (2020),AdaBoost-CNN: An adaptive boosting algorithm for convolutional neural networks to classify multi-class imbalanced datasets using transfer learning, Neurocomputing , Volume 404, 3 September 2020, Pages 351-366.

[21]. Srishti Singh, Amrit Paul, Dr. Arun M,” Parallelization Of Digit Recognition System Using Deep Convolutional Neural Network On CUDA “,2017 IEEE 3rd International Conference on Sensing, Signal Processing and Security (ICSSS), 978-1-5090-4929-5©2017 IEEE,379-383.

[22]. Weiwei Jiang,” MNIST-MIX: a multi-language handwritten digit recognition dataset”, IOP SciNotes 1 (2020) 025002.

[23]. Teddy Surya Gunawan,, Ahmad Fakhrur Razi Mohd Noor,, Mira Kartiwi “Development of English Handwritten Recognition Using Deep Neural Network”, Indonesian Journal of Electrical Engineering and Computer Science Vol. 10, No. 2, May 2018, pp. 562-568.

[24]. Emmanuel Dufourq, Bruce A. Bassett,” EDEN: Evolutionary Deep Networks for Efficient Machine Learning”, arXiv:1709.09161v1 [stat.ML] 26 Sep 2017

[25]. http://yann.lecun.com/exdb/mnist/

[26]. https://www.itl.nist.gov/iaui/vip/cs_links/EMNIST/gzip.zip

[27]. Tiwari Laxmikant, Raja Rohit, Awasthi Vineet, Miri Rohit, Sinha G.R., Alkinani Monagi H., Polat Kemal,”Detection of lung nodule and cancer using novel Mask-3 FCM and TWEDLNN algorithms”,Measurement,vol. 172, 2021, https://doi.org/10.1016/j.measurement.2020.108882.

[28]. Verma Pratibha, Sahu Sanat Kumar, Awasthi Vineet Kumar, “Deep Neural Network With Feature Optimization Technique for Classification of Coronary Artery Disease “,Handbook of Research on Computer Vision and Image Processing in the Deep Learning Era, IGI Global, 2023, DOI: 10.4018/978-1-7998-8892-5.ch016

[29]. sharma hari, brown kate, Awasthi Vineet Kumar,” An interactive weight-based portfolio system using goal programming”, application of mathmetical modelling , machine learning, and intelligent computing for industrial development, CRC press, 2023, ISBN : 978-1-003-38659-9(ebk).

[30]. Verma Pratibha, Sahu Sanat Kumar, Awasthi Vineet Kumar,An Ensemble Model With Genetic Algorithm for Classification of Coronary Artery Disease, International Journal of Computer Vision and Image Processing (IJCVIP) , IGI Global , vol. 11(3), ,2021, DOI: 10.4018/IJCVIP.2021070105.

[31]. Verma, P., Awasthi, V.K., Shrivas, A.K., Sahu, S.K. (2022). Stacked Generalization Based Ensemble Model for Classification of Coronary Artery Disease. In: Misra, R., Kesswani, N., Rajarajan, M., Veeravalli, B., Patel, A. (eds) Internet of Things and Connected Technologies. ICIoTCT 2021. Lecture Notes in Networks and Systems, vol 340. Springer, Cham. https://doi.org/10.1007/978-3-030-94507-7_6.

[32]. Tiwari, L., Awasthi, V., Patra, R.K., Miri, R., Raja, H., Bhaskar, N. (2022). Lung Cancer Detection Using Deep Convolutional Neural Networks. In: Bhateja, V., Khin Wee, L., Lin, J.CW., Satapathy, S.C., Rajesh, T.M. (eds) Data Engineering and Intelligent Computing. Lecture Notes in Networks and Systems, vol 446. Springer, Singapore. https://doi.org/10.1007/978-981-19-1559-8_37

[33]. Sharma Dinesh K. , Hota H.S, Awasthi Vineet Kumar ,” An integrated K-means-GP approach for US stock fund diversification and its impact due to COVID-19”, International Journal of Computational Economics and Econometrics, Vol. 12 (4), pp 381-404, 2022, https://doi.org/10.1504/IJCEE.2022.126317

[34]. Verma P., Awasthi V. K. , Sahu S. K., "Classification of Coronary Artery Disease Using Deep Neural Network with Dimension Reduction Technique," 2021 2nd International Conference for Emerging Technology (INCET), Belagavi, India, 2021, pp. 1-5, doi: 10.1109/INCET51464.2021.9456322.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jul782

[35]. Verma, P., Awasthi, V. K., Sahu, S. K., & Shrivas, A. K. (2022). Coronary Artery Disease Classification Using Deep Neural Network and Ensemble Models Optimized by Particle Swarm Optimization. International Journal of Applied Metaheuristic Computing(IJAMC),13(1),1-25. http://doi.org/10.4018/IJAMC.292504.

[36]. Verma P., Awasthi V. K. , Sahu S. K., "A Novel Design of Classification of Coronary Artery Disease Using Deep Learning and Data Mining Algorithms", Revue d'Intelligence Artificielle Vol. 35(3), pp. 209-215, 2021.

[37]. Hota, H.S., Awasthi, V.K., Singhai, S.K. (2018). Comparative Analysis of AHP and Its Integrated Techniques Applied for Stock Index Ranking. In: Sa, P., Sahoo, M., Murugappan, M., Wu, Y., Majhi, B. (eds) Progress in Intelligent Computing Techniques: Theory, Practice, and Applications. Advances in Intelligent Systems and Computing, vol 719. Springer, Singapore. https://doi.org/10.1007/978-981-10-3376-6_14.

[38]. Ghosh, P., Hazra, S., Chatterjee, S. Future Prospects Analysis in Healthcare Management Using Machine Learning Algorithms. the International Journal of Engineering and Science Invention (IJESI), ISSN (online), 2319-6734.

[39]. Hazra, S., Mahapatra, S., Chatterjee, S., & Pal, D. (2023). Automated Risk Prediction of Liver Disorders Using Machine Learning. In the proceedings of 1st International conference on Latest Trends on Applied Science, Management, Humanities and Information Technology (SAICON-IC-LTASMHIT-2023) on 19th June (pp. 301-306).

[40]. Nitu Saha; Rituparna Mondal; Arunima Banerjee; Rupa Debnath; Siddhartha Chatterjee; (2025) Advanced DeepLungCareNet: A Next-Generation Framework for Lung Cancer Prediction. International Journal of Innovative Science and Research Technology, 10(6), 2312-2320. https://doi.org/10.38124/ijisrt/25jun1801.

[41]. Rupa Debnath; Rituparna Mondal; Arpita Chakraborty; Siddhartha Chatterjee (2025) Advances in Artificial Intelligence for Lung Cancer Detection and Diagnostic Accuracy: A Comprehensive Review. International Journal of Innovative Science and Research Technology, 10(5), 1579-1586. https://doi.org/10.38124/IJISRT/25may1339.

[42]. Hazra,S.,Chatterjee, S.,Mandal, A.,Sarkar, M.,Mandal,B.K.(2023). An Analysis of Duckworth-Lewis-Stern Method in the Context of Interrupted Limited over Cricket Matches. Proceedings of International Conference on Data Analytics and Insights, ICDAI 2023. LNNS, vol 727. Springer, Singapore. https://doi.org/10.1007/978-981-99-3878-0_46.

[43]. Mandal, K.K., Chatterjee, S., Chakraborty, A., Mondal, S., Samanta, S. (2020). Applying Encryption Algorithm on Text Steganography Based on Number System. In: Maharatna, K., Kanjilal, M., Konar, S., Nandi, S., Das, K. (eds) Computational Advancement in Communication Circuits and Systems. Lecture Notes in Electrical Engineering, vol 575. Springer, Singapore. https://doi.org/10.1007/978-981-13-8687-9_23.

[44]. Chatterjee, Siddhartha, A Survey on Data Clustering Approaches (June 17, 2018). IOSR Journal of Business and Management (IOSR - JBM), Journal No. 46879, UGC Serial No. 2953, Impact Factor - 3.52, pp 34 - 42, e-ISSN 2278 - 487X,p-ISSN2319-7668,IOSR .,Availableat SSRN: https://ssrn.com/abstract=3586458.

[45]. Bose, S., Chatterjee, S., Chakraborty, B., Halder, P., & Samanta, S. (2021). An Analysis and Discussion of Human Sentiment Based on Social Network Information. Int. J. HIT. TRANSC: ECCN. Vol, 7(1A), 62-71.