SOFT COMPUTING APPROACHES FOR RECOGNITION OF HANDWRITTEN MATH EQUATIONS.

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Abstract : The recognition of handwritten symbols, numbers, and mathematical expressions is a challenging and inspiring mission due to the varying styles of writing used in documents. It requires a combination of skills and knowledge to perform well. Although there are numerous methods available in the field, none of them can meet the requirements of accuracy, throughput and efficiencies in the recognition of complex equations. The database generated from various writers' strokes, styles, overwriting, and statistical features have been analyzed. A neural network classifier was then used to perform the recognition. The goal of this work is to provide an automatic solution for the recognition of math symbols, numbers, and expressions in various documents such as educational applications, stationery, and postal documents. The system's success rate can be determined by its efficiency, throughput, and identification rate.

***IndexTerms* - math recognition, back propagation neural network (BPNN), Gradient descent, performance.**

I. INTRODUCTION

Today, the recognition of mathematical expressions in meaningful usage is becoming an integral part of the field of mathematics. This discipline is known for its immense contribution to technological development and scientific research. However, it is very challenging to recognize the manually written expressions in the context of machine learning.

Due to the complexity of the language and the 2D spatial arrangement of the data, it is not possible to perform effective analysis. The complexity of the non-linear structure of mathematics makes it hard to inputting and editing the expressions.

There are various factors that affect the quality of the written expressions. Some of these include the way of writing, the impact of noise, the density of letters, and the missing portion. It is very important that the system that will be used to recognize the various math symbols and expressions be developed with a better method. This will allow the user to easily input the mathematical notation into the machine. This work is aims to provide a coherent digitization of the manual math report, which can help the visually impaired people to read it. It can also help them recognize the various mathematical expressions in printed documents and answer sheets.

There are two kinds of processing involved in this process: offline and online. Several work have been carried out for online and offline recognition systems. One of the most challenging tasks involved in this process is pattern recognition, which is mainly related to the recognition of symbols and characters. Researchers have been developing various methods and approaches for this. Due to the complexity of the task, it is still under development. One of the main challenges that the researchers are working on is the recognition of handwritten math expressions. Prior studies in the field of pattern identification were carried out.

The major work in this area was done on the recognition of printed and handwritten letters, symbols, and mathematical expressions. Although the results were generally well-received, there were some drawbacks. For instance, in manual written identification, there was a lack of achievement in identifying complex characters and separated symbols.

Although the main objective of these studies was to improve the accuracy of the process, there are still many problems that remain to be solved. One of these is the implementation of entry constraints.

This can be done through the use of deep neural networks. The results of the studies show that the multi-level extraction of complex symbols with a deep neural network is very efficient and has a high recognition rate. A different extraction method is used for feature recognition.

The recognition rate depends on the features extracted and the classifier used. The performance of artificial neural network is mainly dependent on the feature extracted. The proposed methodology for feature recognition takes into account the various factors that affect the recognition of complex symbols and expressions.

It utilizes a database collected from various writers to analyze the variations in writing styles and strokes. The strategy is then performed on a multi-level framework to improve the performance of artificial neural network.

The features are analyzed with a boundary box etc. The morphological segmentation strategy and a neural network classifier have been utilized for the recognition of simple as well as complicated mathematical equations.

II. DIAGRAMATICAL FLOW OF RECOGNITION.

The various Steps in the recognition have been described as below and related system architecture is depicted in below fig. 1.

2.1 **Image Acquisition:** After scanning a document containing a math equation, various methods of processing it can be applied. However, if the grade of the image has not been up to the mark, the intended tasks might not be achievable.

2.2 **Preprocessing:** Various techniques are used for preprocessing, such as removing the small frequency of image noise, minimizing the intensity, and separating the reflections and masking portions. Binarization can be used to convert a colored or gray image into a white and black one. In addition, variations in the math equations can be taken out by normalizing them. In skeletonization, the shape of the data is then extracted to remove irregularities.

2.3 **Segmentation:** Segmentation is a process that involves simplifying an image into multiple elements. It can be used to make it easier to analyze. It can also detect objects and confine them in the image. A boundary box has been obtained with the morphological segmentation.

2.4 **Feature Extraction:** This process can help improve the accuracy of math equations by identifying the various features of the captured image. It then chooses the components and elements that it considers most appropriate. Due to the complexity of the task, it can be hard to extract the features from the data. Some of the factors that can affect the extraction process include variance, mean, standard deviations, correlation, kurtosis, and entropy.

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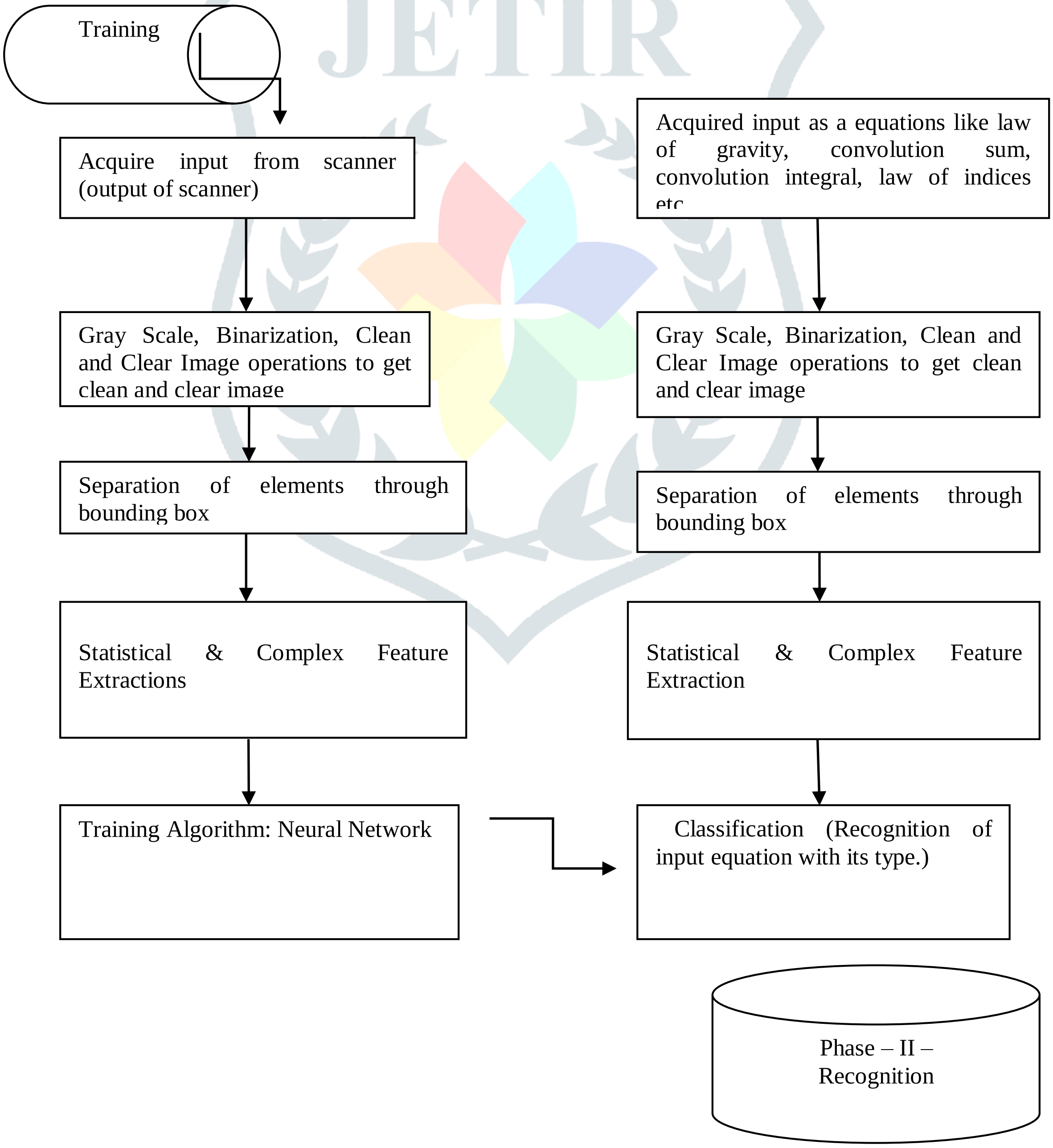

Figure 1: Block Diagram of Math Recognition System.

III. OUTCOMES & DISCUSSION

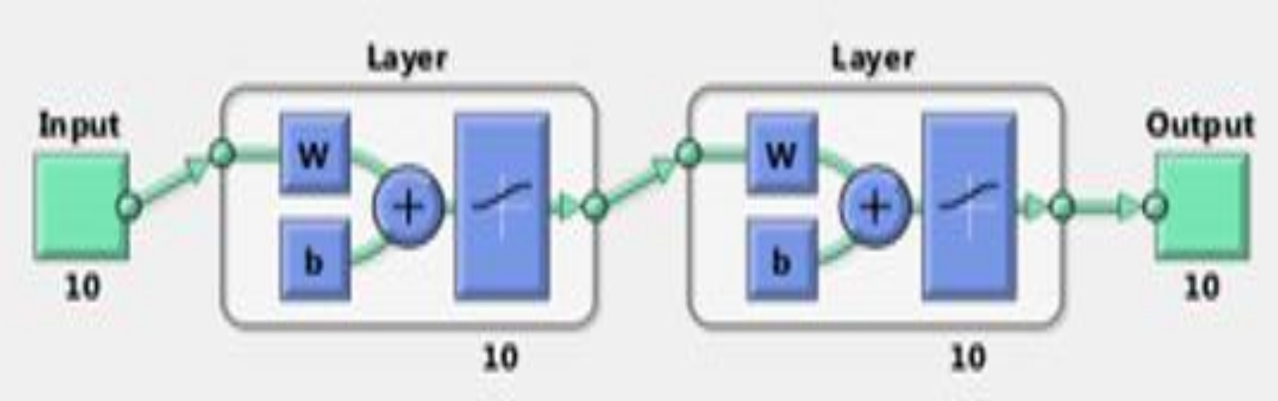

Figure 2 : Neural network architecture

The neural network architecture with number of input layer, hidden layer & output layer. There are ten nodes in each layer as shown in fig. 2. The total nodes cannot be predicted or calculated before training the neural network. The neural network parameters are as shown in table 1. The as actual performance through training state, validation, learning rate etc. are shown in following fig. 3 fig. 4 and fig. 5.

Table 1 Parameters showing the performance.

Sl. No.	Parameters
1	Adaptive learning with Gradient Descent training
2	Sum squared error predicts the performance of network
3	Time : 0 : 00: 01
4	Training :R: 0.88561
5	Net : 5000 epochs (627 iterations)
6	Total Iteration: 627
7	Performance: 8.20
8	Gradient: 9.7984e-07
9	Learning Rate: 10005.8469
10	Computations: MEX

Table 1, shows that the parameter which shows the performance of neural network classifier. It has denoted that the adaptable learning rate has utilized. The total epochs are 5000 and R: 0.88561 at 627 iterations. Mean squared error is calculated to assess regression task in machine learning.

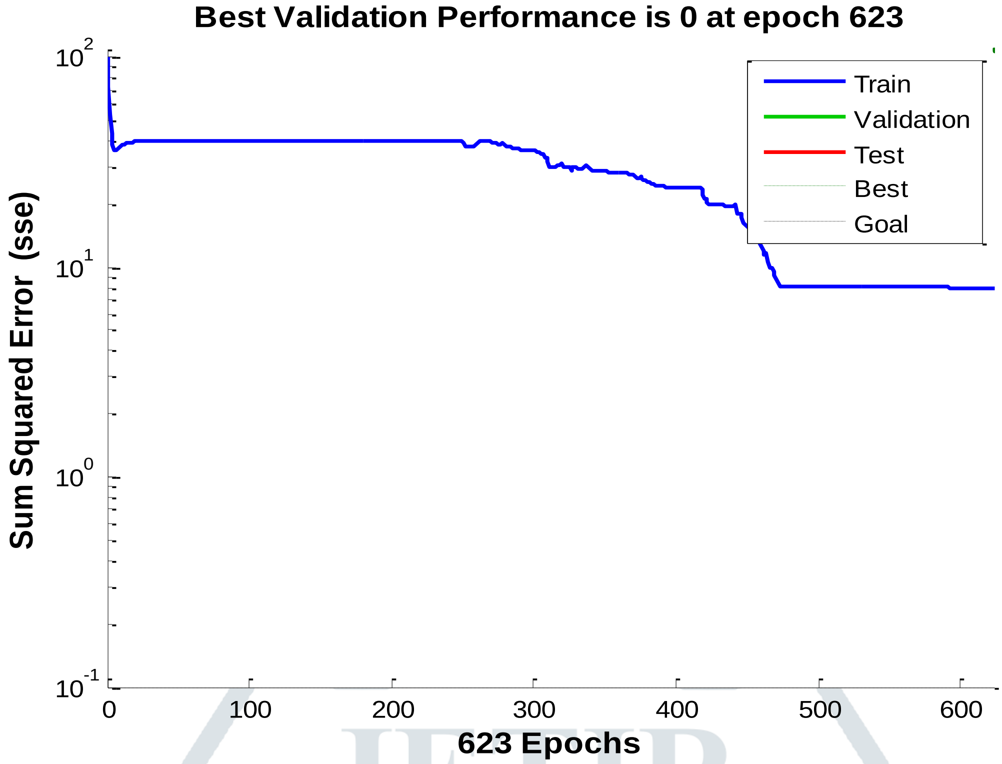

Figure 3: Validations (Epoch Vs Sum squared error)

The best training execution is meet with mean squared is 0.0000 at epoch 623 depicted in fig. 3, it has concluded that sum squared error has reduced with rise in epochs.

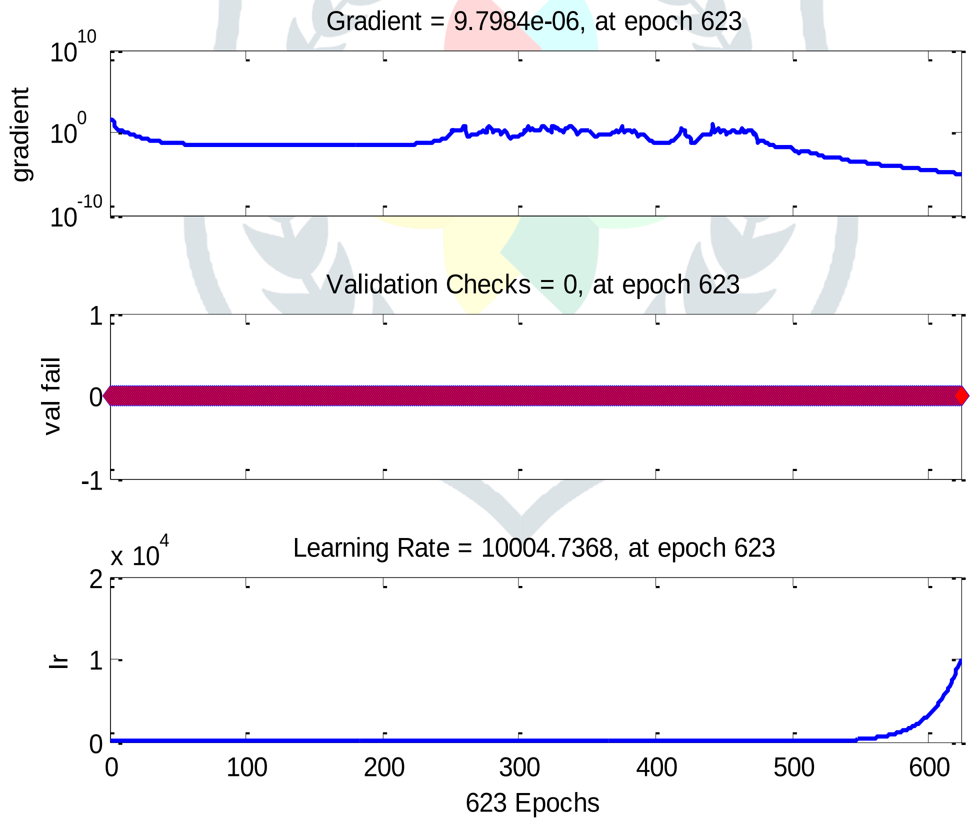

Figure 4 : Neural network gradient & learning rate state

The gradient is 9.79e-06 with 623 epochs as depicted in fig. 4.

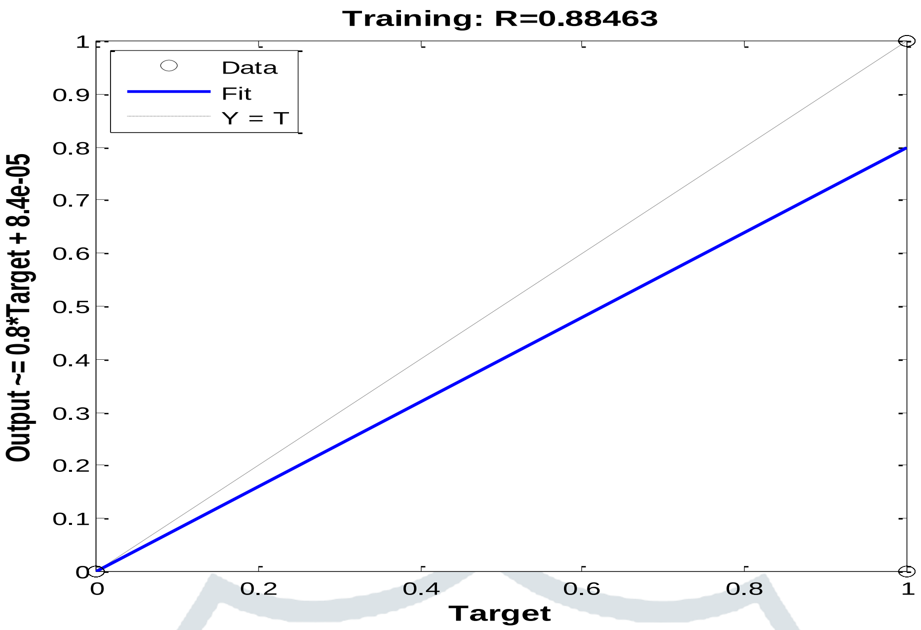

Figure 5: Neural network Training

The target and actual output for training of neural network is R: 0.88463 as depicted in above fig. 5. The contrast in blue color line and dotted line describes the variation between standard training output and practical output. The steps have been described in block diagram and that has depicted in below fig.6

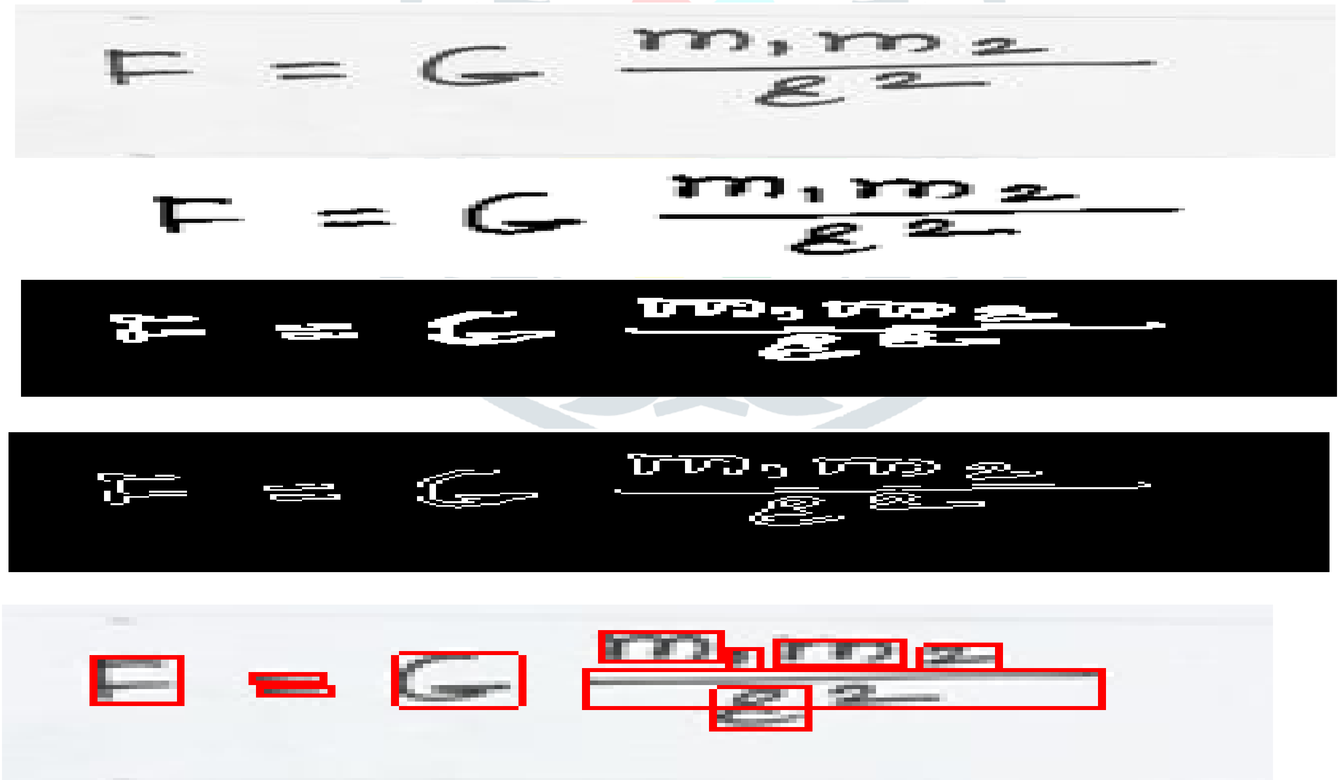

Figure 6: Basic steps in preprocess and segmentation with bounding box.

In fig. 6 as shown above, the different operations from preprocessing through segmentation with bounding box have been carried out for mathematical expressions of newton's law of gravity to get noise free image & isolate each component in equation through boundary box.

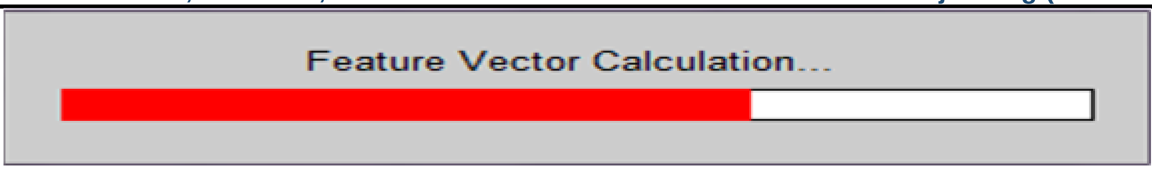

Figure 7: Feature vector.

The statistical & complex features are extracted from the acquired input images for the calculation of feature vector in fig.7. The extracted features are much important for the purpose of validation.

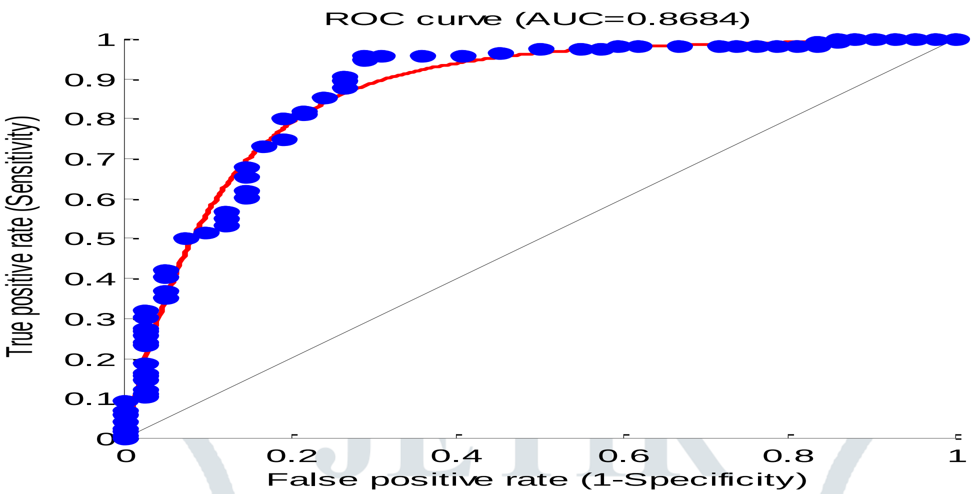

Figure 8: Receiver Operating Characteristics curve

The fig.8 shows, a receiver operating characteristics curve drawn true positive rate (TPR) versus false positive rate (FPR). A model whose chances are 100% incorrect has an Area Under Curve of 0.0 and whose chances are 100% error free has an Area Under Curve of 1.0. In table 2 as shown below, the ROC specifications have mentioned. It has been observed that Area under Curve (AUC) has been observed in which AUC value shows best classification achievement. The sensitivity interval has also been calculated using the given specificity points. The 95% CI is evaluated using 2000 layered bootstraps. The various specifications of this process are shown in the figure below. These include the sensitivity curve, cost effective curve, maximum efficiency curve, and specificity curve.

Table 2 ROC specifications.

Sl. No.	Parameter	Value
1	AUC	0.8763
2	SE	0.0279
3	CI	[0.8246 0.9322]
4	CO	[195 106 149 160]

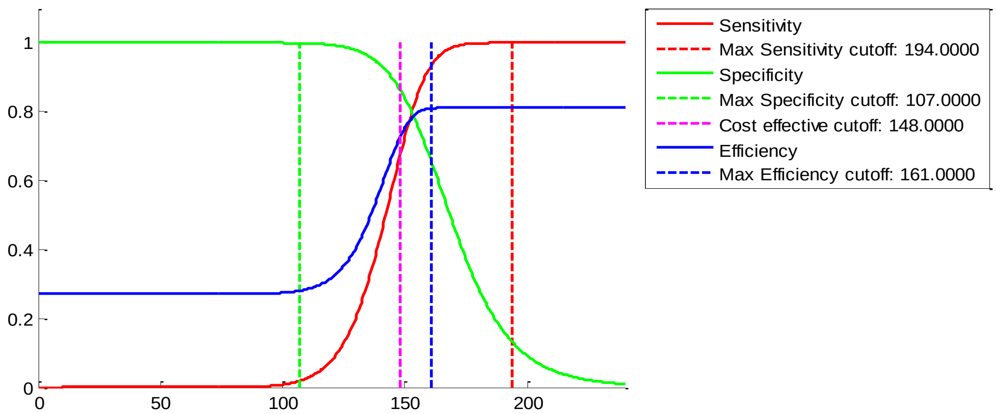

Figure 9: sensitivity, specificity and efficiency

As shown in figure. 9, parameters are determined and mentioned in below table 3.

Table 3: Sensitivity, Specificity and Efficiency

Sl. No.	Parameters with Cut-off point	Value
1	Maximum sensitivity cut off point	194
2	Maximum specificity cut off point	107
3	Cost effective cut off point	148
4	Maximum efficiency cut off point	161

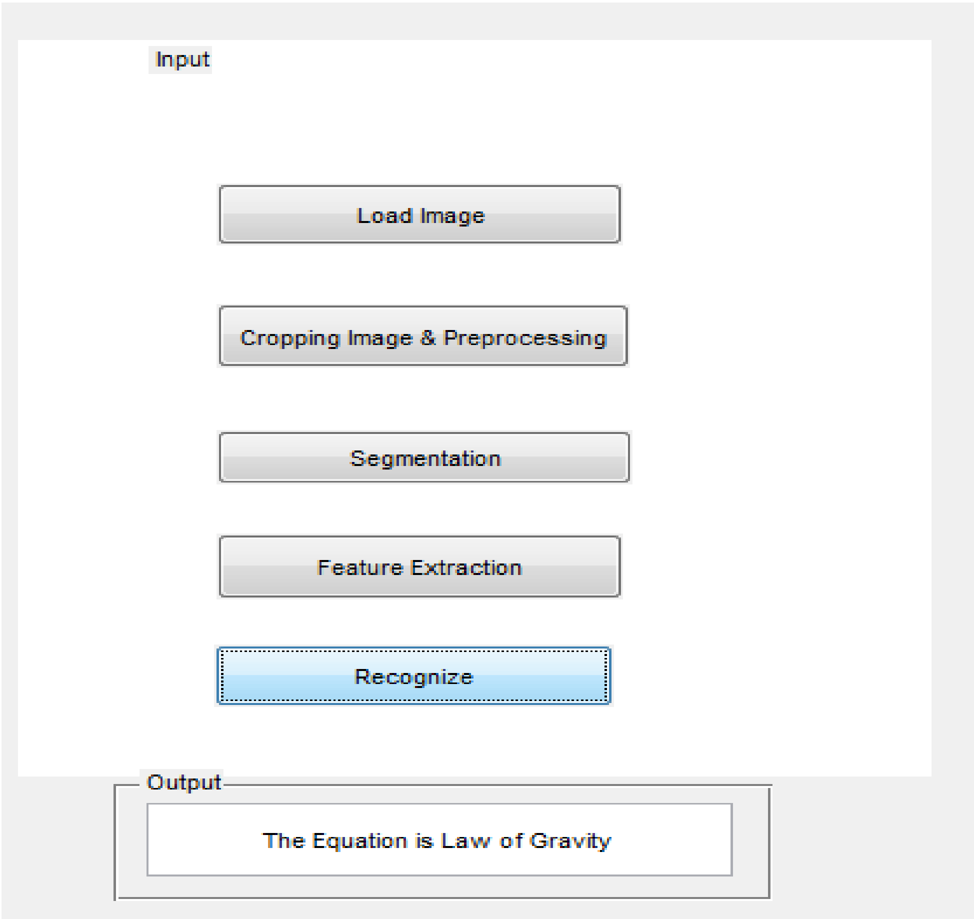

Figure 11: Recognition system through graphical user interface (GUI)

As shown in fig. 11, the complete flow of recognition system from acquired input image through its identification with its name has been described. The recognition of demonstration for the newton's law of gravity has been shown in above figure shows the accuracy of the system.

IV. CONCLUSIONS

Through simulation results, the complex and simple handwritten mathematical expressions were identified and categorized. The performance of the system has improved due to the use of neural network as a classification and feature extraction tool. The results of the analysis show that the accuracy of the system is 88%. The achievement of the system has been explained through the receiver operating characteristics curve area.

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