MATHEMATICAL HANDWRITTEN RECOGNITION

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ABSTRACT

A Mathematical Handwritten Recognition system is being developed to convert handwritten mathematical notations into digital form, aiming traditional pen-and-paper math symbols with modern digital platforms. This system utilizes advanced machine learning methods and deep neural networks for sequence recognition, enhancing accessibility and productivity in education and professional settings. The project addresses challenges such as different handwriting styles and unclear symbols, for real time processing for fast and precise recognition. End-to-end approaches and multi-modal input methods are emphasized, along with UI design considerations to enhance user experience. The paper discusses evaluation criteria, benchmark datasets, and practical applications across various domains. Future research directions are outlined to further advance handwritten mathematical expression recognition, contributing to the digitization of mathematical communication and improving accessibility for a wide range of users.

Keyword : - *Recognition, Open benchmark datasets, Capabilities, Digitization, advancements*

1. INTRODUCTION

With the advent of modern technologies like digital pens, tablets, and smartphones, the use of digital documents has surged. However, scientific documents often incorporate diagrams and equations, which are essential for conveying complex problems and theories using universally understood languages. These notations rely on a two-dimensional layout, where symbols are arranged in a structured manner. Mathematical notation, in particular, plays a crucial role in various scientific fields. To leverage pen-based technologies effectively, there's a need to develop systems capable of translating handwritten content (in its physical form) into digital text (in its logical form). This task is challenging due to the stochastic nature of handwriting and the diversity in writing styles. Handwriting recognition has been an active area of research since the 1960s, aiming to address this difficulty. In recent years, significant advancements have been made in text recognition systems, facilitating the transition from physical to digital formats.

Recognizing handwritten mathematical symbols presents numerous challenges, particularly distinguishing between symbols such as dots and commas, which play critical roles in notation but can be difficult to differentiate. These symbols serve various functions depending on context, like representing decimal points, multiplication operators, or annotations, leading to potential ambiguity issues. The spatial relationships among symbols further complicate matters due to their free placement and alignment, including superscripts and subscripts with different fonts and typefaces. Our research focuses on developing a system for recognizing handwritten mathematical expressions using desktop or laptop systems. Our proposed model aims to segment and classify symbols into categories such as Latin variables, Greek letters, and Special Symbols. We utilize the ELM algorithm for symbol recognition and convert the classified results into LATEX format widely used for documentation. Previous studies have predominantly focused on recognizing handwritten alphabets and numbers, but the recognition of handwritten mathematical expressions, with their diverse fonts and types, has gained increasing attention. This recognition has applications across various fields, as mathematical expressions can be complex two-dimensional structures with spatially arranged characters and symbols of different sizes. While symbol recognition tends to perform well, structural analysis remains challenging, especially with improperly typeset or handwritten expressions. The applications of mathematical expression recognition span scientific document digitization, information retrieval, and enhancing accessibility for the visually impaired. Off-line recognition addresses both printed and handwritten representations of mathematical expressions, typically involving symbol recognition and structural analysis stages.

Expressions can be presented in two formats: embedded, where they are mixed with text and referred to as inline expressions, and displayed, where they are typed on separate lines. The focus lies on feature extraction, gathering information about objects or groups of objects for classification. Handwritten expression recognition by machines has been a central focus in pattern recognition. This involves an online approach to converting handwritten mathematical expressions into equivalent expressions in typesetting command languages like TEX or MathML. The problem is divided into three modular sub-problems: isolated symbol classification, expression partitioning, and parsing. This division allows for independent solving and evaluation of each sub-problem, enabling improvements in each area while maintaining system integrity.

Mathematical symbols can be written beside above, or below in various sizes, fonts, and typefaces. MathML and LaTeX require knowledge of predefined sets of keywords. Several commercially successful products recognize users' natural handwriting for simple tasks. Handwritten mathematical expression recognition is a fascinating and challenging research area in image processing and pattern recognition. Data is collected from different users with different handwriting styles. Recognizing mathematical formulas is crucial in scientific fields as they constitute a fundamental part of notation. In offline recognition, handwritten or printed formulas are presented as bitmaps, a static representation of the data, while online recognition systems store data as digital ink, a dynamic representation essentially consisting of a sequence of points with temporal information.

1.2 ADVANTAGES:

The advantages of mathematical handwritten recognition lie in its ability to bridge the traditional and digital realms of mathematical expression. Firstly, it enhances accessibility by allowing handwritten mathematical content to be easily converted into digital format, making it readily available across platforms and devices. Secondly, it improves productivity by automating the process of digitization, saving time and effort otherwise spent on manual data entry. Additionally, it facilitates collaboration by enabling seamless sharing and communication of mathematical ideas and equations in digital form. Moreover, the technology supports personalized learning experiences by providing tailored feedback and assistance based on individual handwriting styles and preferences. Furthermore, mathematical handwritten recognition systems can be integrated into existing software applications and educational platforms, enhancing their functionality and value. Overall, the advantages of mathematical handwritten recognition include accessibility, productivity, collaboration, personalization, and integration capabilities, making it a valuable tool in various contexts.

1.3 APPLICATIONS:

Mathematical handwritten recognition finds application across diverse domains including education, where it aids students in digitizing notes and equations for improved organization and sharing. Additionally, professionals in engineering and science benefit from converting hand-drawn sketches and formulas into digital formats for analysis and documentation. Content creators utilize the technology to streamline design processes by converting hand-drawn sketches into digital assets, while individuals with disabilities benefit from alternative input methods. Moreover, researchers leverage handwritten recognition systems for benchmarking algorithms and exploring new techniques. In fields requiring mathematical communication, such as economics and finance, these systems facilitate the exchange of handwritten expressions in digital formats, enhancing productivity and collaboration. Overall, mathematical handwritten recognition enhances accessibility, productivity, and communication across various sectors.

2. LITERATURE SURVEY

The existing system are still far from perfection because of challenges that arise from the two-dimensional nature of mathematical input and the large symbol set with many similar looking symbols. The symbol recognition rate achieved using raw images as local off-line features along the pen-tip trajectory by BLSTM significantly outperformed Handwritten Mathematical Recognition. [1]. Although several results were reported in the literature, progress was unclear due to the absence of common datasets and evaluation metrics. To overcome this bottleneck, the Competition on Recognition of Handwritten Mathematical Expressions was introduced as a shared task [2]. We have required that this classifier has the capability to reject invalid symbol segmentation hypotheses, where the input does not correspond to an actual symbol. System performance is improving relative to previous competitions. Data and evaluation tools used for the competition are publicly available [3]. Track Attend Parse (TAP) is an end-to-end neural network for recognizing online handwritten math expressions. It uses a tracker for input tracing and a parser with guided hybrid attention. Can implement an end-to-end neural network for recognizing online handwritten math expressions. Can use bidirectional recurrent neural networks with gated recurrent units for tracing and a parser with guided hybrid attention for generating LATEX notations.[4]. It introduces a deep convolutional neural network for detecting small and challenging handwritten symbols. The detected symbols are then subjected to structural analysis using the DRACULAE parser, known for its high accuracy. Employ a deep convolutional neural network for detecting small symbols and use the DRACULAE parser for accurate structural analysis, given correct symbol detection. Integrate both components for a robust recognition system [5]. Encoder-decoder models have made great progress on handwritten mathematical expression recognition recently. However, it is still a challenge for existing methods to assign attention to image features accurately. Moreover, those encoder-decoder models usually adopt RNN-based models in their decoder part, which makes them inefficient in processing long LATEX sequences [6]. Compared to several methods that do not use data augmentation, experiments demonstrate that our model improves the Exp Rate of current state-of-the-art methods on CROHME 2014 by 2.23%. Similarly, on CROHME 2016 and CROHME 2019, we improve the Exp Rate by 1.92% and 2.28% respectively [7]. In past, Convolutional Neural Network, also called CNN, has been highly used for recognizing patterns. In this paper, We propose an idea to recognize HME and evaluate offline using CNN for classification [8]. This solution can be made even better by recognizing more complex mathematical equations like differential integral equations and trigonometry, recognizing chemical equations and recognition of cursive handwriting where the character [9]. A distinctive part of the survey is that we also considered how UI design relies on the use of different recognition approaches, which is aimed at helping potential researchers improve the performance of the introduced approaches toward the best responses in practical applications. Finally, this paper presents the prospective survey of future research directions in handwritten mathematical expression recognition and their applications. Mathematical typesetting systems and editors such as LATEX are widely used for formatting mathematical expression.[10]. We also compare our results to other systems; experimental evaluation suggests that CNNs are a powerful tool for handwritten mathematical expression recognition. The goal of this research is to give a general overview of handwritten mathematical expression recognition and its applications. We will take this technology and implement it to recognize a handwritten mathematical expression on a paper and solve it using a mobile application, to improve the user interface and interactivity [11].

3. OBJECTIVE AND METHODOLOGY

3.1 OBJECTIVES

- Achieve high levels of accuracy in recognizing handwritten mathematical symbols, equations, and expressions to ensure reliable conversion to digital format.
- Enable real-time or near-real-time processing of handwritten content to provide fast recognition capabilities, supporting efficient workflow and user interaction.
- Develop recognition systems that can adapt to different handwriting styles, variations in symbol representation, and diverse input formats to accommodate a wide range of users.
- Recognize various types of mathematical notations, including symbols, equations, diagrams, and annotations, to support diverse applications and use cases across different domains.
- Enhance robustness against noise, distortion, and other factors that may affect recognition accuracy, ensuring reliable performance in various environments and conditions.

3.2METHODOLOGY

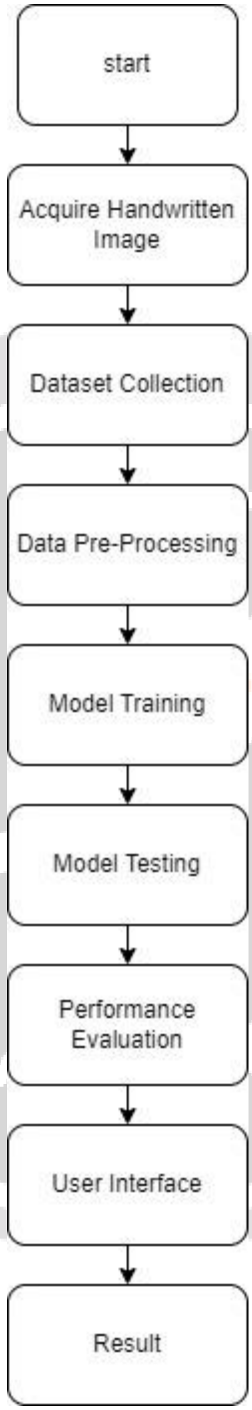

Figure 1. Proposed methodology for Mathematical Handwritten Recognition

3.2.1 Dataset Collection :

Dataset collection for mathematical handwritten recognition involves sourcing diverse handwritten samples of mathematical expressions for training and evaluating recognition models. The data collection process encompasses criteria such as diversity in handwriting styles, languages, and mathematical symbols, while also addressing ethical considerations and data privacy. Annotation and labeling ensure ground truth for model training and evaluation, with preprocessing steps like image normalization enhancing dataset quality. Splitting the dataset into training, validation, and test sets is crucial, guided by strategies to maintain data integrity and generalization performance. The dataset for the project is collected from Kaggle which is an online platform for data enthusiasts and data scientists. The data is made sure that it diverse and is a combination of various handwriting styles and also contains various labelled datasets which would be helpful in training and testing the model.

3.2.2 Data Pre-processing :

Data preprocessing is a crucial step in preparing raw data for mathematical handwritten recognition tasks. The quality and suitability of the data greatly influence the performance of recognition models. Before proceeding with any analysis or modeling, it is essential to clean the data to remove noise, so noise reduction is done to remove unwanted noise from the image so that the image would be suitable for further process. Also image enhancement is done to make the image suitable for training and testing to yield higher accuracy. If the input image contains multiple expressions, horizontal line segmentation algorithms come into play. These algorithms isolate individual expressions for independent processing, allowing the system to focus on one expression at a time.

3.2.3 Model Training :

LeNet-5 model is used for the model. It stands as a pioneering convolutional neural network (CNN) architecture primarily designed for handwritten digit recognition, notably on datasets like MNIST. Comprising layers of convolutional and pooling operations, LeNet-5 begins with convolutional layers extracting features like edges and textures, followed by pooling layers subsampling the extracted features. This is succeeded by fully connected layers, progressively reducing the dimensionality of the data and eventually classifying it into distinct categories. Activation functions, typically sigmoid or tanh, introduce nonlinearity throughout the network. The output layer employs a softmax function to yield probabilities for each class. Although considered relatively simplistic compared to contemporary CNN architectures, LeNet-5 was pivotal in demonstrating CNNs' efficacy for image recognition tasks, particularly in handwritten digit recognition, laying the groundwork for subsequent advancements in the field.

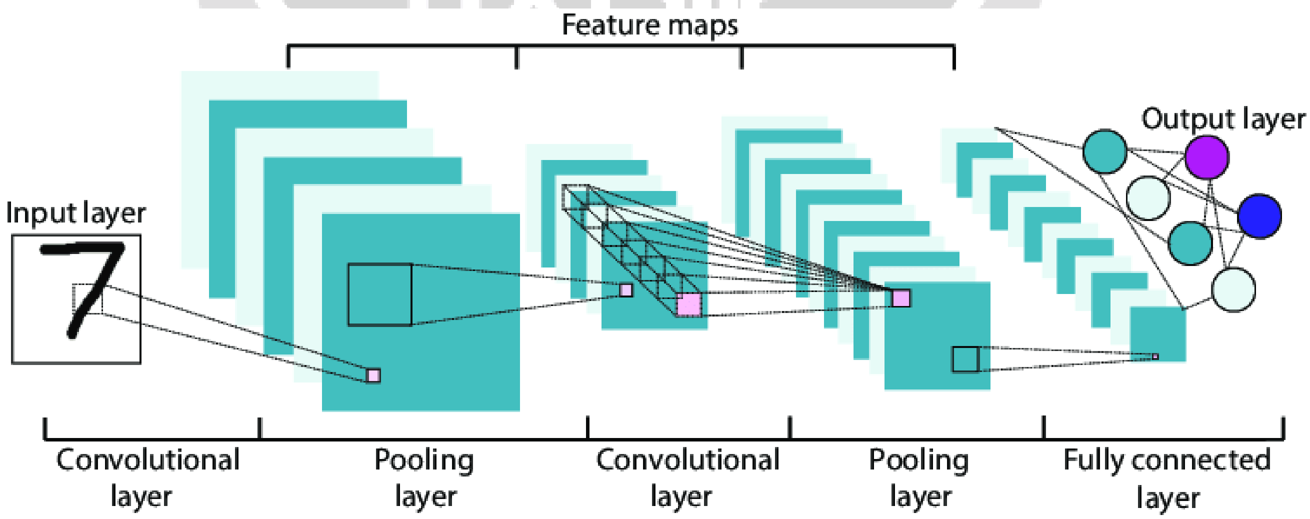

Figure-2 - LeNet-5 Architecture

4. RESULTS AND DISCUSSIONS

The implementation of the Mathematical Handwritten Recognition system yielded promising outcomes, demonstrating its effectiveness in accurately transcribing handwritten mathematical expressions into digital formats. The performance of the system was evaluated using a diverse dataset comprising handwritten mathematical expressions encompassing a wide range of complexities and writing styles.

4.1 Performance Evaluation :

Accuracy: Accuracy stands as a fundamental and intuitive metric for evaluating the performance of classification models and it is a measure of the model's ability to make correct predictions compared to the total number of predictions made. Mathematically, accuracy is calculated as the ratio of correct predictions to the total number of predictions, expressed as a percentage. Mathematically, accuracy is calculated as:

$$\text{Accuracy} = ((TP+TN))/((TP+TN+FP+FN))$$

4.2 Results

The implementation of the Mathematical Handwritten Recognition system yielded promising outcomes, demonstrating its effectiveness in accurately transcribing handwritten mathematical expressions into digital formats. The performance of the system was evaluated using a diverse dataset comprising handwritten mathematical expressions encompassing a wide range of complexities and writing styles. The system achieved an accuracy of 86.83%. The test results of the model are as follows:

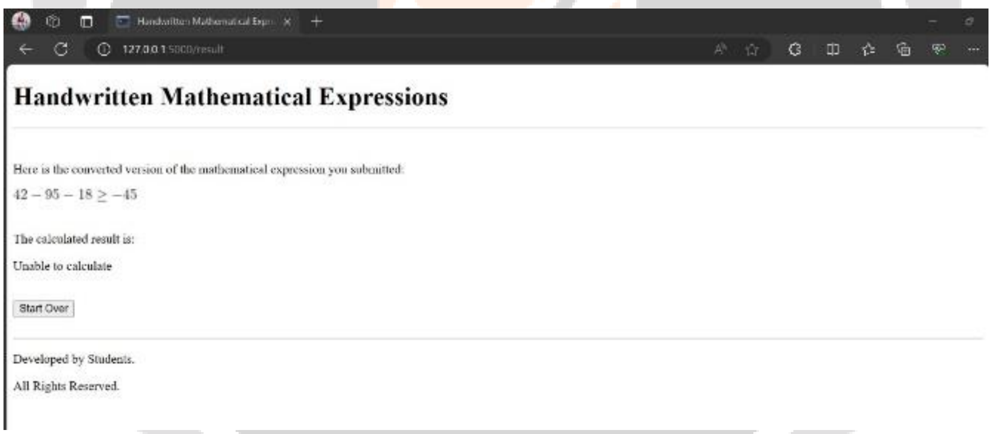

Figure 3- Result-1

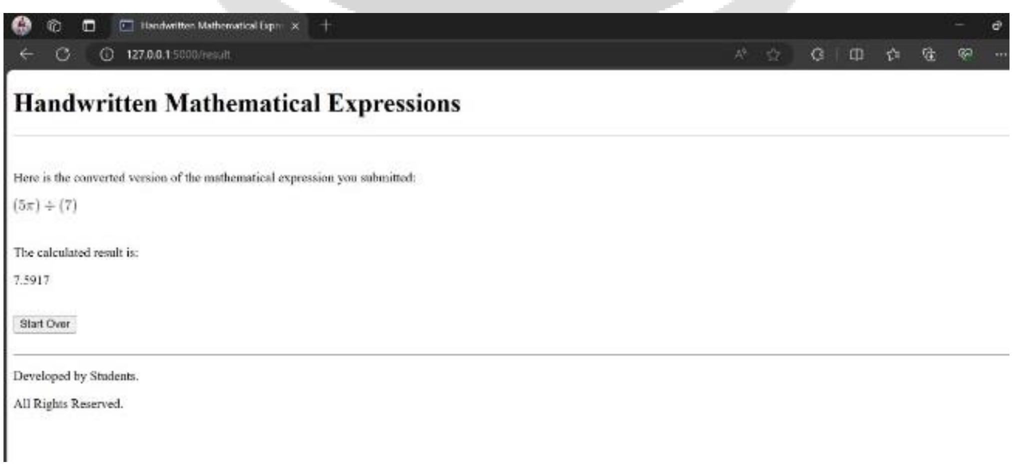

Figure 4- Result-2

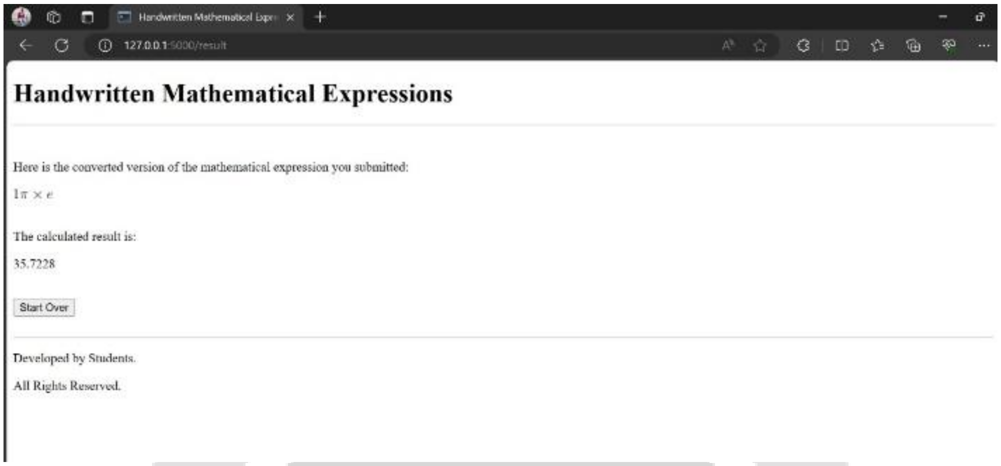

Figure 5- Result-3

5. REFERENCES

[1]. Shi Y, H. LI, and F. K. SOONG, "A Unified Framework for Symbol Segmentation and Recognition of Handwritten Mathematical Expressions", presented at the Ninth International Conference on Document Analysis and Recognition (ICDAR 2007), Parana, pp. 854-858, doi: 10.1109/ICDAR.2007.4377036, (2007).

[2]. Awal A M, H. Mouche`re, and C. Viard-Gaudin, "Towards Handwritten Mathematical Expression Recognition", presented at the 10th International Conference on Document Analysis and Recognition, Barcelona, pp.1046-1050, doi: 10.1109/ICDAR.2009.71, (2009).

[3]. L. Dsouza and M. Mascarenhas, "Offline Handwritten Mathematical Expression Recognition using Convolutional Neural Network", presented at the International Conference on Information, Communication, Engineering, and Technology (ICICET), pp.1-3, doi:10.1109/ICICET.2018.8533789 (2018).

[4]. Hu Y, L. Peng, and Y. Tang, "On-line Handwritten Mathematical Expression Recognition Method Based on Statistical and Semantic Analysis", presented at the Document Analysis Systems (DAS), 2014 11th IAPR International Workshop on, Tours, 2014, pp.171-175, doi: 10.1109/DAS.2014.47, (2014). [5]. Lee, G., Nho, K., Kang, B., Sohn, K.-A. & Kim, D. Predicting Alzheimer's disease progression using multi-modal deep learning approach. *Sci. Rep.* 9, 1952 (2019).

[5]. Khanh Minh Phan, Anh Duc Le, Bipin Indurkhya, Masaki Nakagawa, "Augmented incremental recognition of online handwritten mathematical expressions", published in the International Journal on Document Analysis and Recognition (IJDAR), 21(4), pp:253-268, 2018, doi:10.1007/s10032-018-0306-1.

[6]. J. Zhang, J. Du, and L. Dai, "Track, Attend, and Parse (TAP): An End-to-End Framework for Online Handwritten Mathematical Expression Recognition", published in IEEE Transactions on Multimedia, vol. 21, no. 1, pp.221-233, 2019, doi: 10.1109/TMM.2018.2844689.

[7]. F. Alvaro, J. A. Sanchez, and J. M. Benedi, "Offline Features for Classifying Handwritten Math Symbols with Recurrent Neural Networks", presented at the Pattern Recognition (ICPR), 2014 22nd International Conference on, Stockholm, 2014, pp. 2944-2949. doi: 10.1109/ICPR.2014.507, (2014).

[8]. J. Zhang, J. Du, and L. Dai, "Multi-Scale Attention with Dense Encoder for Handwritten Mathematical Expression Recognition", presented at the 2018 24th International Conference on Pattern Recognition (ICPR), Beijing, 2018, pp. 2245-2250., doi: 10.1109/ICPR.2018.8546031.

[9]. Kam-Fai Chan and Dit-Yan Yeung, "Mathematical Expression Recognition: A Survey", published in the International Journal on Document Analysis and Recognition, 3(1), pp.3–15, (2000).

[10]. FF. Alvaro, J. A. S´nchez, and J. M. Benedi, "Recognition of Printed Mathematical Expressions Using Two-Dimensional Stochastic Context-Free Grammars", presented at the International Conference on Document Analysis and Recognition, Beijing, pp. 1225-1229, doi: 10.1109/ICDAR.2011.247, (2011).

[11]. Utpal Garain and B.B. Chaudhuri, "A corpus for OCR research on mathematical expressions", published in the International Journal on Document Analysis and Recognition, pp.241-259, Springer, (2004).

[12]. Manisha Bharambe, "Recognition of Offline Handwritten Mathematical Expressions", presented at the National conference on Digital Image and Signal Processing (DISP2015), Pune, published in the International Journal of Computer Applications, pp.35-39, (2015).

[13]. Sanjay S. Garde, Pallavi V. Baviskar, and K. P. Adhiya, "Identification of Handwritten Simple Mathematical Equation Based on SVM and Projection Histogram", published in the International Journal of Soft Computing and Engineering (IJSCE), 3(2), ISSN: 2231- 2307, (2013).

[14]. Anita Jindal, Renu Dhir, and Rajneesh Rani, "Diagonal Features and SVM classifier for Handwritten Gurumukhi Character recognition", published in the International Journal of Advance Research in Computer science and software engineering, 2(5), (2012).

[15]. G. Huang, G.-B. Huang, S. Song, and K. You, "Trends in Extreme Learning Machines: A Review", published in Neural Networks, 61(1), pp.32-48, (2015).

[16]. G.B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme Learning Machine for Regression and Multiclass Classification," published in IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics, 42(2), pp.513-529, (2012).