

Mathematical Equation Identification and Solving System

Riya Tambe¹, Rakhi Bharadwaj², Sanaya Vaze³, Varad Uttarwar⁴ and Samarth Urane⁵

¹Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India
Email: riya.tambe21@vit.edu

²⁻⁵Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India
Email: {rakhi.bharadwaj, sanaya.vaze21, varad.uttarwar21, samarth.urane21}@vit.edu

Abstract— The rapid advancements in deep learning techniques have significantly impacted various fields, including mathematics and natural language processing. Mathematical equation identification and solving is a challenging task that has been studied by researchers for many years. Traditional approaches to this task typically rely on rule-based systems, hand-crafted features or manual work. However, these approaches are often limited in their ability to handle complex equations and there are also chances of error in it. The survey begins by discussing the challenges associated with mathematical equation identification and solving, such as the complexity of mathematical notation, variable representation, and equation structure. The paper provides an overview of the existing methodologies, algorithms, and frameworks employed in the development of systems capable of identifying and solving mathematical equations using deep learning techniques.

Index Terms— Machine learning, Image processing, Character recognition, Symbol recognition, Equation parsing

I. INTRODUCTION

Mathematical equations serve as fundamental tools for expressing quantitative relationships in various scientific, engineering, and mathematical domains. The ability to accurately identify and solve equations is crucial for problem-solving, scientific discovery, and educational advancement. Traditional methods of equation identification and solving, while effective, often require significant manual intervention and domain expertise. With the rapid advancement of deep learning techniques, there is a growing interest in developing intelligent systems that can automate and enhance the process of mathematical equation identification and solving.

Over the past few years, there has been a significant increase in research focusing on the integration of deep learning, natural language processing, and mathematics. This has given rise to innovative systems that specialize in identifying and solving mathematical equations using deep learning techniques. By harnessing the capabilities of neural networks, semantic comprehension, and contextual analysis, these systems have the potential to transform multiple industries, such as education, scientific research, and engineering design. Their primary goal is to simplify and democratize the equation-solving process, making it more user-friendly and accessible to a wider range of individuals.

Creating such systems poses several challenges. Mathematical notation can differ greatly, and equations can range from basic algebraic expressions to intricate differential equations. Ensuring accurate recognition and proper

interpretation of these various notations is a complex task. Moreover, generating dependable solutions that humans can easily understand requires a thorough understanding of mathematical concepts and effective problem-solving approaches.

This paper aims to give a detailed overview of the research on systems that use deep learning to identify and solve mathematical equations. By examining the methods, algorithms, and progress in this field, this survey seeks to provide insights into the current state of the art, the challenges faced by researchers, and the possibilities for future advancements. By bringing together the knowledge in this area, we hope to contribute to the development of intelligent systems that can effortlessly recognize and solve mathematical equations, making it easier to understand and work with mathematical problems.

II. RECENT WORK

A. Using Projection profile and Support vector machine (SVM)

In this work different steps or phases of recognition process for simple mathematical handwritten equations are described. Which includes pre-processing, segmentation, feature extraction, classification and recognition. Projection profile is used for extracting features from the equation and Support Vector Machine (SVM) is used for classification.

Following are phases of this work:

Pre-processing: The raw handwritten mathematical equation data undergoes preprocessing steps like smoothing, enhancing, filtering, and image cleanup to ready it for character analysis. This process generates a refined digital image that contributes to improved classification accuracy.

Segmentation: Segmentation divides a document image into uniform image units via pixel groups. Bounding box distribution confirms accurate non-cursive character segmentation. Labeling connected components operates on binary images, assigning values to same-area pixels. Grayscale conversion precedes segmented image generation using automatic global thresholding and binarization.

Feature Extraction: Feature extraction extracts vital information from text images for character recognition. A coherent, representative feature set is crucial for pattern recognition. Projection histograms count "1" pixels in various directions: horizontal, vertical, left diagonal, and right diagonal.

Classification: Classification is the pivotal stage in Optical Character Recognition (OCR), using extracted features to identify text segments. Support Vector Machines (SVM) are a supervised learning method for classification and regression. SVM constructs a decision model to predict new sample categories based on their positions in space relative to a gap that separates different categories.

In order to improve the accuracy and recognition rates of identifying handwritten mathematical symbols, this study suggests using projection histograms as a powerful method for extracting features and recommends the adoption of support vector machines (SVMs) as a suitable classification technique. By combining these two approaches, they have achieved better results in recognizing handwritten mathematical symbols.

The provided dataset comprises 237 symbols sourced from 28 distinct simple mathematical equations. Employing projection profile and support vector machine methods, two datasets are identified, yielding recognition rates of 97.58% and 98.40%. The average recognition rate for these datasets collectively stands at 98.26% for handwritten mathematical equations.

However, this paper has some limitations such that it Only considers simple mathematical expressions. Performance on more complex expressions is not reported. The method is not yet robust to noise and variations in handwriting styles.

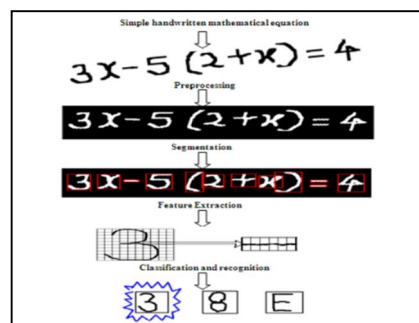


Figure 1. Overview of equation recognition process

B. Using Convolutional Neural Networks

This paper introduces an innovative method to address the task of solving handwritten mathematical equations. The method comprises two primary stages: (i) segmentation of the equations and (ii) the actual equation solving process. During the equation segmentation stage, the algorithm initially breaks down the equation into its fundamental components, including figures, variables, operators, and various symbols. Subsequently, in the equation solving phase, a hybrid approach involving both symbolic and numerical techniques is employed to arrive at a solution. This project involved steps like Binarization, Line Segmentation, Character Segmentation as a part of preprocessing. In the actual implementation after pre processing, it uses two models, Dense and RNN. RNN is used to predict results of current operation with respect to previous ones. This uses Flask, Keras and TensorFlow. **Dataset** - The training data for the model includes the Modified National Institute of Standards and Technology (MNIST) dataset, along with a custom-made dataset containing symbols for mathematical operators like "-", "+", "/", "*", "(", and ")".

Accuracy - While the paper lacks quantitative performance metrics, it does provide illustrative sample outputs that demonstrate the model's capability to accurately recognize and solve basic equations. One thing to note is that this model allows simple equations. The system needs to be further developed for complex equations.

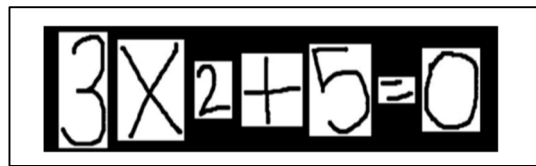


Figure 2. Processed image

TABLE I. MODEL USED V/S ACCURACY

Sr. no	Model	Accuracy
1.	Dense Model (Simple Equation)	98%
2.	RNN Model (Simple Equation)	96%
3.	CNN Model (Complex Equation)	85%

C. Using Convolutional Neural Networks with more Complex outputs

The paper presents an innovative approach for transforming handwritten mathematical expressions into machine-readable text. This is achieved through a process involving horizontal and vertical projection for segmentation, coupled with the utilization of a convolutional neural network for character recognition. The method effectively achieves segmentation and accurate recognition of handwritten equations even when presented on lined paper, subsequently converting them into a digital format.

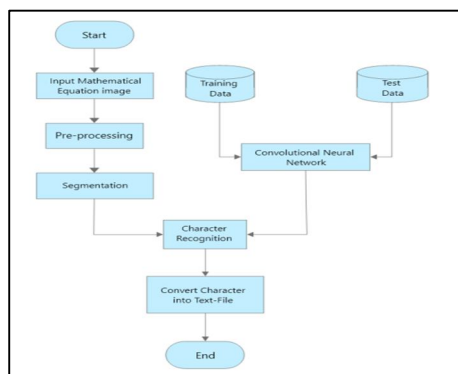


Figure 3. Flowchart of said project

This entire work involves preprocessing of the data at first (that is done after the mathematical equation is scanned); then, segmentation is done which is line and character segmentation. Meanwhile, the CNN model is trained in two different datasets – training and testing datasets. The characters are converted to text-files at the end.

The paper uses the CROHME dataset, which contains 10,000 different images, to train the network for character recognition. 1000 images from each number from 0-9 are extracted from the dataset and saved to a separate file for training and testing purposes.

60 of the images are used to train the network, while 40 are used to test the accuracy. The dataset is used to train a convolutional neural network (CNN) for character classification using MATLAB's neural network toolbox .

Accuracy - The CNN was able to classify numbers from 0-9 with a test accuracy of 85% using 600 images for training and 400 images for testing .

The model's ability to accurately segment equations with overlapping square root characters and identify equals characters without further segmentation demonstrated its effectiveness.

Future scope or improvements - The paper recognizes the potential for enhancing the precision of the proposed model, particularly in the character recognition stage that employs a convolutional neural network (CNN). Addressing the segmentation of handwritten mathematical equations proves to be a demanding task due to the variability in handwriting styles, instances of character overlap, and variations in symbol sizes. However, the paper falls short of offering a comprehensive resolution to tackle these intricate challenges.

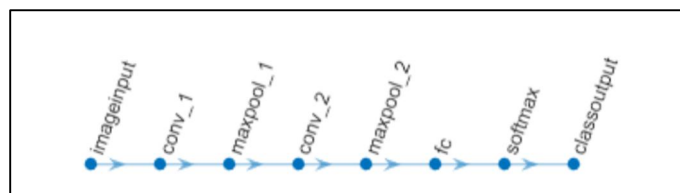


Figure 4. CNN network architecture

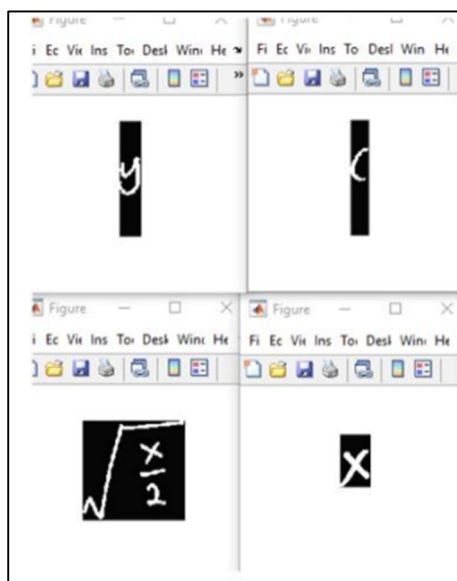


Figure 5. Character segmentation

D. OFR system

Within the pages of the paper, a thorough exploration takes place concerning the OFR system—an innovative framework designed for the extraction and comprehension of mathematical expressions embedded within various documents. The system's specific emphasis lies in its adeptness at decoding two-dimensional expressions, a category encompassing intricate mathematical constructs such as vectors and matrices.

A primary avenue of investigation pursued by the authors centers on the implementation of graph grammar and the concept of graph rewriting. These facets serve as pivotal components in the proposed solution, aimed at

overcoming challenges inherent in the recognition of two-dimensional mathematical notations. Particularly, these challenges encompass the complexities introduced by ambiguities existing between distinct grammar rules, as well as the intricate task of effectively constructing and deconstructing graphs that accurately represent the underlying mathematical structures.

This dual-pronged approach delves deep into the intricacies of capturing and decoding the nuanced intricacies of two-dimensional mathematical expressions. The utilization of graph grammar stands as a strategic choice, offering a systematic framework to disambiguate grammar rules that might otherwise lead to misinterpretations. Simultaneously, the integration of graph rewriting techniques holds the potential to facilitate the construction of comprehensive and accurate graphical representations of the mathematical content, providing a tangible bridge between textual input and visual output.

In sum, the paper embarks on an intellectual journey through the realm of the OCR system's capabilities, rooted in its advanced proficiency to extract, comprehend, and distinguish intricate two-dimensional mathematical expressions. The exploration of graph grammar and graph rewriting significantly contributes to the understanding of how this system addresses the complexity of recognizing and faithfully representing these expressions, even in the presence of rule ambiguities and intricate graph constructions.

The scholarly document elaborates upon the adept application of graph grammar and the associated mechanism of graph rewriting, aptly positioned as a compelling solution to effectively discern and decode the intricacies of two-dimensional mathematical notations.

Encompassing a multifaceted architecture, the system designated for the recognition of mathematical formulas—dubbed OFR (Optical Formula Recognition)—comprises three distinct components, each serving as a pivotal source of requisite information that substantiates and augments the overall process of recognition.

Embedded within this system is a bottom-up parsing algorithm, strategically employed to navigate the intricate landscape of mathematical expressions. Anchored in contextual cues, this algorithm systematically applies a set of rules, leading to the identification of nodes that correspond to relevant elements of the expression. Upon the successful alignment of nodes, a pivotal collapsing procedure is initiated, effectively fusing matched nodes into coherent entities. This dynamic process further extends to the manipulation of outgoing connections, updating linkages to account for the immediate neighborhood of nodes.

The crux of the algorithm lies in its innate capacity to facilitate localized treatment of the document's mathematical expressions. In effect, this approach elegantly mirrors the nuanced perception employed by human observers when engaging with intricate formulas. This unique attribute underpins the algorithm's efficacy in faithfully mirroring the intricacies of visual interpretation, paralleling human cognitive processes in a manner that befits the complexity of mathematical notations.

In summary, the paper embarks on a comprehensive exposition, shedding light on the symbiotic relationship between graph grammar, graph rewriting, and the intricate domain of two-dimensional mathematical expressions. The innovative architecture of the OFR system, underscored by its tripartite components, in tandem with the dynamic bottom-up parsing algorithm, illuminates the nuanced process of recognition. Ultimately, this multifaceted approach stands as a testament to the amalgamation of technical prowess and cognitive alignment, allowing the system to effectively decipher, recognize, and appropriately render the intricate tapestry of mathematical formulas.

The specific dataset employed for the mathematical formula recognition system is not explicitly detailed within the confines of the paper. Nonetheless, the discourse within the paper meticulously delves into the utilization of lexical units, often referred to as tokens, as integral elements within the intricate parsing process.

While the precise nature of the dataset remains undisclosed, the paper casts a spotlight on the paramount role that lexical units, representing individual symbols embedded within the document, play in facilitating the overarching parsing process. These tokens, positioned as critical units of textual representation, function as the fundamental building blocks upon which the parsing algorithm operates. The algorithm intricately navigates the ensemble of tokens, employing contextually derived rules to dissect the mathematical expressions encapsulated within the document.

By strategically leveraging the distinctive attributes inherent in these tokens, the parsing mechanism proficiently assembles and reassembles constituent parts of the mathematical expressions. This process resonates as an embodiment of cognitive faculties, mimicking human cognition in an algorithmic fashion. The intricate interplay between tokens and parsing rules serves as the cornerstone of the mathematical formula recognition system's effectiveness, transmuting raw symbolical data into coherent and intelligible representations.

In summation, while the paper refrains from explicitly unveiling the specifics of the utilized dataset, it illuminates the pivotal importance of lexical units, or tokens, within the parsing process. This contextualizes the symbiotic relationship between tokens and parsing rules, wherein the former acts as the elemental canvas upon which the

algorithmic dissection of mathematical expressions occurs. Through this lens, the paper offers a lens into the synergy of token-based parsing, further underscoring the system's intrinsic alignment with the cognitive nuances of human mathematical interpretation.

The paper draws attention to a critical drawback prevalent in existing methodologies for mathematical recognition, particularly in their struggles to effectively analyze intricate two-dimensional expressions such as vectors and matrices. As a direct response to this deficiency, the presented system takes center stage, aspiring to surmount these inherent limitations and offer a viable solution.

However, it's worth noting that the paper does not delve into either quantitative or qualitative assessments of the system's performance. Key evaluation parameters, including accuracy, efficiency, and robustness, remain conspicuously absent from the discourse. This omission stands as a notable gap in the comprehensive evaluation of the system's prowess. While the paper succeeds in highlighting the necessity for addressing the challenges posed by complex mathematical expressions, the absence of empirical evidence to substantiate the system's effectiveness leaves a void in our understanding of its real-world applicability and capabilities.

Future scope - The paper acknowledges the issue of ambiguities arising from the interplay of grammar rules and the intricate graph construction process. However, it refrains from delving into a detailed exposition of the specific challenges or limitations entailed by these complex concerns.

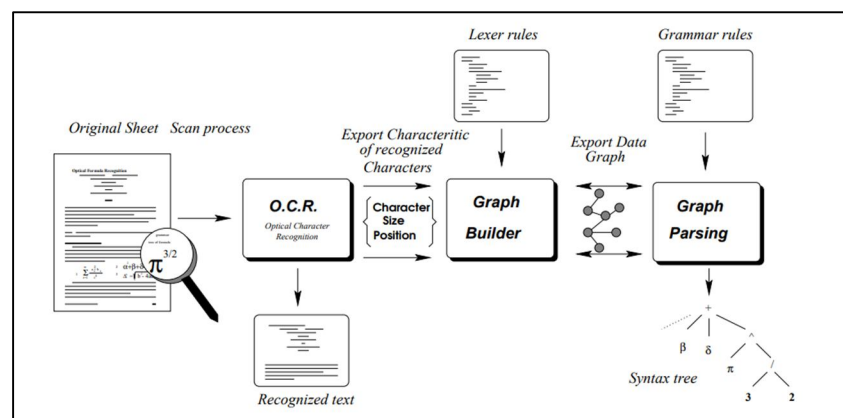


Figure 6. The process of OCR

E. Comparative study between ANN and SVM-

The central objective of the paper is to undertake a comprehensive comparison of the recognition rates pertaining to handwritten mathematical symbols. This comparative analysis is executed across a diverse set of descriptors, namely GIST, PHOG, SURF, and Centrist, each hailing from distinct computational frameworks. Furthermore, this investigation encompasses the utilization of two distinct classifiers: the potent Artificial Neural Network and the robust Support Vector Machines.

In essence, the study embarks on an ambitious journey to unravel the intricate nuances of symbol recognition through the lens of these descriptors and classifiers. This endeavor hinges on evaluating their respective efficacies, thereby contributing valuable insights into the optimal choices for symbol recognition tasks that are intrinsic to various computational and machine learning applications.

Within the realm of the paper's investigation lies the strategic application of an assemblage of four distinct descriptors—namely GIST, PHOG, SURF, and Centrist—in the critical task of feature extraction for the recognition of handwritten mathematical symbols. This meticulous selection of descriptors brings to the forefront a diversified toolkit of computational approaches, each poised to contribute a unique facet to the overarching recognition process.

Furthermore, the study introduces a dichotomy in the form of two potent classifiers, namely the Artificial Neural Network (ANN) and the Support Vector Machines (SVM). These formidable classification algorithms are strategically harnessed to navigate the intricacies of the symbol recognition process. Their distinct methodologies and inherent capabilities are seamlessly integrated into the framework, marking a decisive step towards the realization of a comprehensive recognition mechanism.

In essence, the paper embarks on a multi-dimensional exploration that traverses descriptor selection, feature extraction, and classifier implementation. This intricate interplay amplifies the depth of understanding in the realm of symbol recognition, while concurrently enhancing the appreciation for the nuanced amalgamation of descriptors and classifiers within the context of mathematical symbol recognition.

While the paper refrains from explicitly disclosing the precise dataset leveraged for the recognition of handwritten mathematical symbols, it does shed light on a pivotal aspect of the data preprocessing methodology. Specifically, the database at hand is meticulously categorized into eight distinctive classes. This strategic classification serves as a proactive measure aimed at enhancing accuracy and mitigating errors stemming from the inherent similarities that often exist between various symbols.

Although the specific dataset remains discreet, the approach of segmenting it into discrete classes speaks to the meticulous consideration of the intricacies associated with symbol recognition. By judiciously categorizing the database, the paper lays the foundation for an augmented recognition process—one that is fortified against the potential pitfalls induced by symbol likeness. This strategic maneuver underscores the paper's commitment to precision and highlights the sophistication of the study's methodology in dealing with the complexities of symbol recognition.

The combination of the GIST descriptor with both Artificial Neural Networks (ANN) and Support Vector Machines (SVM) achieved a recognition rate of 99% .

The PHOG descriptor combined with SVMs achieved a recognition rate of 98%, while with ANN it achieved a recognition rate of 90% .

The Centrist descriptor combined with SVMs achieved a recognition rate of 79%, while with ANN it achieved a recognition rate of 72%.

The SURF descriptor combined with SVMs achieved a recognition rate of 73%, while with ANN it achieved a recognition rate of 65%

The paper does not address the potential influence of variations in symbol sizes on the overall performance of the recognition process. Additionally, there is an absence of information regarding the specific dataset employed for both training and testing the system. This absence of dataset details could potentially impact the broader applicability and generalizability of the outcomes presented in the paper.

Furthermore, the paper omits any discussion about the computational resources that the recognition process necessitates. Critical aspects like processing time and memory consumption, which play a pivotal role in evaluating the practical feasibility of the system, remain unexplored within the paper's discourse.

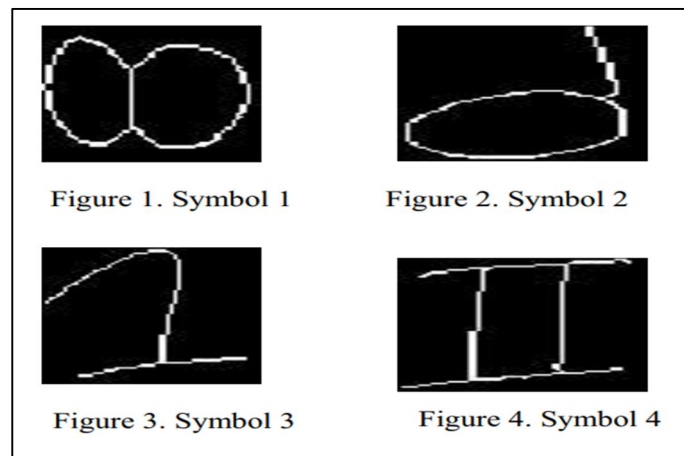


Figure 7. Symbol segmentation

TABLE II. ANN V/S CNN RECOGNITION RATE

ANN		SVM	
Descriptor	Recognition Rate	Descriptor	recognition rate
GIST	99%	GIST	99%
PHOG	90%	PHOG	98%
Centrist	72%	Centrist	79%
SURF	65%	SURF	73%

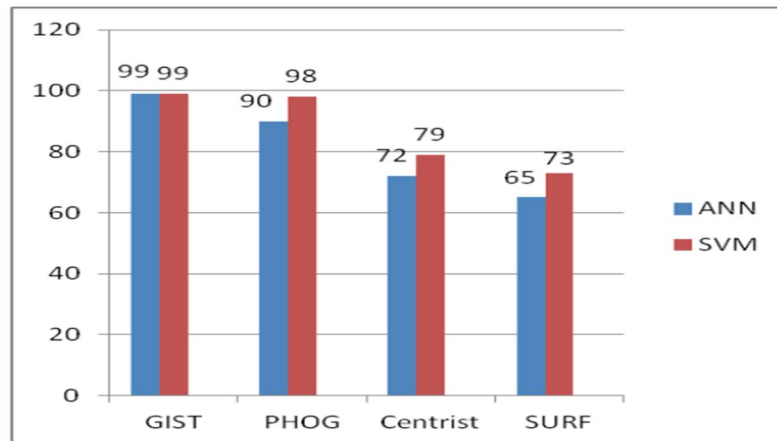


Figure 8. Graph of ANN v/s SVM

III. RESEARCH GAP

The field of handwritten mathematical equation recognition presents both challenges and opportunities for innovation. While existing approaches contribute valuable insights, overarching research gaps remain that hinder the advancement of accuracy and robustness in recognition systems. A notable limitation is the recognition of complex mathematical expressions involving symbols, fractions, exponents, and intricate structures. Current methods often focus on simpler equations, leaving uncertainty about their ability to handle more intricate and diverse notations. Furthermore, the effectiveness of these methods in accommodating a wide range of handwriting styles remains a critical concern. The variability in individual writing styles necessitates techniques that can adapt and ensure accurate recognition.

Another challenge lies in the segmentation process—a pivotal step in equation recognition. While proposed methods excel in segmenting equations with distinct symbol separations, issues arise when symbols overlap or touch. This challenge is exacerbated with handwritten equations exhibiting irregularities in spacing and symbol placement. Accurate segmentation of equations with varying spacing and overlapping characters requires further investigation.

Moreover, approaches utilizing Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) lack transparency in decision-making, posing a research gap in interpretability. Understanding how these models recognize specific symbols is vital for trust-building and error rectification. Addressing these overarching research gaps will pave the way for improved accuracy, robustness, and practicality in recognizing handwritten mathematical equations.

IV. PROPOSED METHODOLOGY

The research project employs two essential datasets, CROHME and MNIST, each contributing unique characteristics and challenges to the task of mathematical equation recognition. The CROHME dataset is a rich resource encompassing over 10,000 handwritten mathematical expressions, thoughtfully contributed by hundreds of writers hailing from diverse geographical locations. These expressions are a collective amalgamation of data from three distinct CROHME competitions, resulting in a dataset that captures a broad spectrum of handwriting styles and mathematical notations. The methodology for preprocessing the CROHME dataset involves a series of critical steps. Initially, images are read and visualized to gain an understanding of their inherent characteristics. Following this, a grayscale transformation is applied to standardize the image format, and binarization simplifies them into a binary representation for subsequent processing. Dilution along both the x and y axes is carried out based on a thresholding mechanism, facilitating the separation of individual characters within the equations. Further, equations are meticulously segmented, and regions of interest (ROI) are meticulously extracted for each symbol present within every equation.

In conjunction with the CROHME dataset, the project leverages the MNIST dataset, a well-known benchmark in the field of handwritten digit recognition. MNIST comprises a collection of handwritten digits ranging from 0 to 9, with a total of 60,000 training images and 10,000 test images. The preprocessing workflow for MNIST, while

simpler compared to CROHME, is equally vital. It involves fundamental steps such as grayscale conversion and binarization to ensure uniformity and compatibility with the chosen classification algorithm. Both datasets, CROHME and MNIST, share a common thread when it comes to the classification algorithm employed—a Convolutional Neural Network (CNN). CNNs are particularly suited for image recognition tasks due to their innate ability to autonomously extract hierarchical features from data, rendering them an ideal choice for predicting the presence of specific mathematical symbols within the provided images.

Collectively, these comprehensive preprocessing steps and the utilization of CNN-based classification comprise the crux of the project's methodology. This approach promises to yield highly sophisticated and accurate results in the identification of mathematical equations and symbols. The applications of this research extend across various domains, including optical character recognition and advancements in educational technology, making it a valuable contribution to the field of machine learning and computer vision.

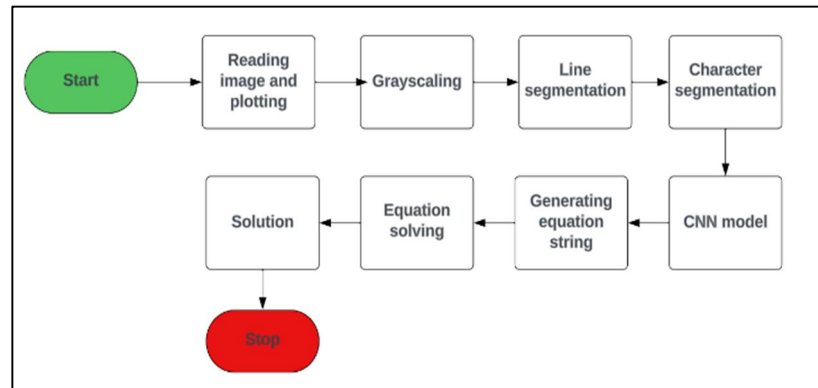


Figure 9. Flowchart of proposed methodology

V. CONCLUSION

Based on a comprehensive literature survey focused on the identification and solving of mathematical equations, it becomes apparent that the integration of deep learning techniques, specifically Convolutional Neural Networks and Support Vector Machines, etc. has propelled the field to new horizons. These advanced methodologies showcase promising capabilities in precisely recognizing and solving mathematical equations.

Conventional methods, relying on rule-based systems and manual interventions, often struggle with intricate equations and are vulnerable to errors. However, the synergy of deep learning, natural language processing, and mathematics has ushered in a new era of intelligent systems that are adept at automating and enhancing the equation-solving process.

The scrutinized studies illuminate various methodologies, algorithms, and frameworks embraced by these systems. Techniques including pre-processing, segmentation, feature extraction, and classification play pivotal roles in achieving precise equation recognition and solving.

Moreover, a notable research gap emerges concerning the interpretability mentioned algorithms. Gaining insights into the decision-making processes of these models is imperative for building trust and rectifying potential errors.

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