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Optimized convolutional neural network enabled technique for sentiment analysis from social media data

Chinta Veena[1], Kavita A. Sultanpure[2], Meenakshi[3], Sunil L. Bangare[4], Punam Sunil Raskar[5], Shriram Sadashiv Kulkarni[4], Myla M. Arcinas[6], Kantilal Pitambar Rane[7]
[1]Department of Computer Science and Engineering, PVKK Institute of Technology, Anantapuramu, India
[2]Department of Information Technology, Vishwakarma Institute of Technology, Savitribai Phule Pune University, Pune, India
[3]School of Journalism and Mass Communication, Apeejay Stya University, Sohna Haryana, India
[4]Department of Information Technology, Sinhgad Academy of Engineering, Savitribai Phule Pune University, Pune, India
[5]Department of Computer and Electronics and Telecommunication Engineering, Smt. Kashibai Navale College of Engineering, Savitribai Phule Pune University, Pune, India
[6]Department of Sociology and Behavioral Sciences, De La Salle University, Manila, Philippines
[7]Department of Electronics and Telecommunications Engineering, Bharati Vidyapeeth College of Engineering, Navi Mumbai, India

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ABSTRACT

Sentiment analysis is an area of computational linguistics that studies natural language processing. The most significant subtasks are gathering people's thoughts and organizing them into groups to determine how they feel. The primary purpose of sentiment analysis is to determine whether the individual who created a piece of material has a positive or negative opinion about a subject. It has been claimed that sentiment analysis and social media mining have contributed to the recent success of both private sector and the government. Emotional analysis has applications in practically every aspect of modern life, from individuals to corporations, telecommunications to medical, and economics to politics. This article describes an improved sentiment analysis model based on gray level co-occurrence matrix (GLCM) texture feature extraction and a convolutional neural network (CNN). This model was created using tweets. First, texture characteristics are extracted from the input data set using the GLCM technique. This feature extraction improves categorization accuracy. CNNs are used to classify objects. It outperforms both the support vector machine and the AdaBoost algorithms in terms of accuracy. CNN has achieved an accuracy of 98.5% for sentiment analysis task.

Corresponding Author:

Chinta Veena
Department of Computer Science and Engineering, PVKK Institute of Technology
Sanapa Road, Rudrampeta, Anantapuramu, Andhra Pradesh, India
Email: cveena30@gmail.com

1. INTRODUCTION

During the course of human history, several innovations have been created to boost agricultural output while also decreasing the amount of time and energy needed for farming. Yet, the enormous population rate thwarted all of their efforts [1]. The estimated global population of 9.8 billion in 2050 is a rise of around 25% from the current population of 7.2 billion [2]. The majority of the aforementioned increase is expected to occur in developing countries. Contrarily, the trend of urbanisation is likely to speed up, with more than “70%” of the world's population (now 49%) forecast to reside in cities by 2050 [3]. Furthermore, incomes will be several times what they are now, driving up demand for food everywhere but especially in developing countries. Because of this, people in these nations will pay more attention to what they eat and how healthy it is, which might lead to a change in preference away from wheat and grains and towards legumes and ultimately, meat [4].

In its broadest sense, the term "sentiment" may refer to a wide range of mental states, such as attitudes, emotions, points of view, and postures. People are increasingly using platforms such as blogs, social media, review sites, and rating systems to voice their opinions and share their experiences in light of the proliferation of the internet. This influx of textual information makes it necessary to conduct research into the significance of emotional expression and to derive actionable conclusions for the purpose of business research [5]. When launching new products, services, or marketing initiatives, businesses, and marketing agencies frequently make use of sentiment analysis [6].

In recent years, there has been a meteoric rise in the quantity of data that contains the viewpoints of social media users. As a direct consequence of this growth, the professional realm has now arrived at its zenith. Emotions experienced by humans are mirrored in public opinion and sentiment, and the effects of these shifts have been felt in the economic and social institutions of almost every contemporary nation. In addition to user reviews that are available to the general public, companies may also have access to information via other internal channels, such as emails sent by customer care representatives, online forums, and surveys [7]. It has been stated that applications of sentiment analysis and social media mining have also helped to the recent success of both private enterprise and the government. Emotion analysis has applications in almost every facet of contemporary life, from individuals to businesses, from the field of telecommunications to that of medicine, and from the realm of economics to that of politics. As a consequence of this, scholars from subjects as varied as economics, sociology, management, and politics in addition to those from the field of computer science applications have contributed to the domains of sentiment analysis and opinion mining. Studies in sentiment analysis probably wouldn't have experienced such a significant spike in popularity if it weren't for their efforts. In point of fact, the impact of fields that cross disciplinary boundaries has resulted in improved algorithmic advancement in the work of sentiment analysis, which in turn led to the development of the idea of "social media analytics" in the preceding decade [8].

The author's personality and the experiences they've had in life are shown in great detail via the information that they share on social media. People are able to be more candid about their thoughts and feelings on social networking sites because of the anonymity that the internet provides [9]. Software companies often make use of data analysts in order to evaluate the status of their competitors. These evaluations are helpful to them in the process of developing new products, developing strategies for promoting those products, and managing their connections with customers. Sentiment analysis offers a wide range of other possible applications, including but not limited to the following: online awareness campaigns; electioneering; the healthcare industry; social event planning; language learning; and social media marketing and sales. The dramatic rise in popularity of the internet among businessmen has directly led to transformations in both the economic and social structures that exist today [10].

Deep learning (DL) is an algorithmic subfield at the cutting edge of the field of machine learning that relies heavily on the concepts underlying neural networks. It makes use of a layer architecture that enables multiple processing, which in turn makes it possible for supervised as well as unsupervised learning of data representations [11]. It is important to note that DL techniques for sentiment analysis have achieved extensive use because they can learn automatically thanks to automated feature learning. This allows them to develop discriminative and exploratory input representations from data. This has contributed to their widespread use. The recent growth in multiclass classification training data as well as the achievements of word embedding’s have also contributed to their widespread use. The capability of the GPU to speed up matrix manipulation is another factor that has been driving the rise in popularity of DL methods. Recent ideas for DL approaches have been used for emotion analysis the majority of the time. The effectiveness of this approach in sentiment analysis has been demonstrated by a large number of studies. Two examples of challenges that have been overcome by these researchers include domain adaptation, which makes it possible for the topic to adapt to context, and modelling long-range dependencies, which can change the polarity of a statement [12].

This article presents gray level co-occurrence matrix (GLCM) texture feature extraction and convolutional neural network (CNN) enabled optimized model for sentiment analysis. In this model, tweets are given as input. Firstly, GLCM algorithm is used to extract texture features from the input data set. This feature extraction helps in achieving higher classification accuracy. Classification is performed using CNN. It achieves higher accuracy than the support vector machine (SVM) and AdaBoost algorithm.

2. LITERATURE SURVEY

A multilayer perceptron model was presented for sentiment classification [13]. A decision tree (DT)-based feature ranking was also offered for feature selection. In addition, the author suggested a hybrid method for weight optimization that is based on differential evolution and the genetic algorithm. This approach is intended to improve multilayer perceptron neural networks. IMDb data is used to test the efficacy of the strategy that was just suggested. A feed-forward neural network is referred to as a multilayer perceptron. This kind of network comprises of one or more hidden layers in addition to input and output layers. A multilayer perceptron is characterised by having multiple layers of nodes, each of which is a neuron that has a non-linear activation function in levels other than the input layer. A method known as supervised learning is what we use while training this sort of network. The author's primary contribution to the proposal of this method is the use of DT-based feature ranking and multilayer perceptron to categorise featured textual material. After being tested on social media at the document level, the DL-based sentiment analysis that was suggested was found to attain performance accuracy of up to 83.25%. The assessment of the suggested method was not carried out using data that was collected in real time.

A DL-based sentiment analysis (SA) of a text was suggested [14]. Their method used the combination of DL recurrent neural networks (RNN) and DT. The author was able to attain computational efficiency by using the strategy that was presented. The analysis of sentiment included in movie review papers was performed using this method. The author's primary contribution to the proposal of this method is the use of word embedding for the purpose of feature extraction and RNN for the purpose of sentiment classification. The method that was presented was tested using a dataset from the movie domain at the document level, and it was able to obtain performance accuracy of up to 89.8%. The evaluation of the suggested method was not carried out using real-time social media.

Convolution long short-term memory (ConvLSTM) neural network architecture is a mix of CNN and long short-term memory (LSTM), both of which are pre-trained vectors. Zharmagambetov and Pak [15] suggested the DL strategy for SA for short text by applying this neural network architecture. The IMDB and Stanford Sentiment Treebank (SSTb) datasets are used in the application of this model. The author's primary contribution to the proposal of this method is the creation of pre-trained word vectors for use in feature extraction, as well as a composite DL model for use in the classification of textual data from the movie domain. At the phrase level, the suggested method was tested using the IMDb and SSTb datasets, and it was found to attain performance accuracy of up to 88.3%. The methodology wasn't tested on either real-time data or social media in order to complete the review.

A DL model known as the CNN was suggested [16] for the purpose of semantic modelling of phrases of various lengths. The DL model was put to the test in a total of four different experiments, including binary and multi-class sentiment prediction, six-way question categorization, and sentiment prediction on twitter. The primary addition made by the author's suggested approach is a description of a dynamic CNN that makes use of a k-max pooling operator as a non-linear subsampling function. Word vectors that have already undergone training are a part of the feature extraction process. High levels of performance are achieved by the network in the six-way question categorization and twitter sentiment prediction tasks. The accuracy of the performance results in 93%, and 87.4% correspondingly. The methodology that was provided was tested on a data set from the movie domain at the phrase level on social media platforms like Twitter.

CNNs were suggested [17] for the purpose of text categorization, specifically for the classification of sentiment. These networks receive input in the form of high-dimensional sparse vectors. As an alternative to using a low dimensional dense vector as input, this model makes use of a bag of words conversion in the convolution layer. The primary contribution made by the author in order to propose this method is the utilisation of a high-dimensional sparse vector as the input for a CNN. This network makes use of the one-dimensional structure of text data in order to make an accurate prediction of sentiment. The document-level efficacy of the DL-based sentiment analysis method that was suggested was tested using IMDb and Amazon product reviews, respectively, for movies and electronic goods. The performance accuracy that was reached was up to 86.6%, and it was 83.9% for electronic product reviews and movie reviews correspondingly.

Johnson and Zhang [18] suggested the use of recursive neural networks with a variety of various topologies for doing sentiment analysis on tweets. One hidden layer recursive neural network, two hidden layers recursive neural network, and recursive neural tensor network were the three types of recursive neural network structures that were used in the process of executing a job involving sentiment analysis. The primary contribution made by the author in order to propose this method is the use of Glove word vectors as input for sentiment categorization, together with a variety of various recursive neural network designs. The suggested models were tested on tweets that included sentences. Using recursive neural networks with one and two layers as well as recursive neural tensor networks, the researchers were able to reach a performance accuracy of up to 63.71% and 59.3%, respectively, for the models.

RDSA framework, which was based on the 'Recommend Me' app, was offered as a recommender system in the cloud [19]. This system was created by applying the DL idea to the sentiment analysis process. The LASA framework served as the basis for the construction of this suggested framework. DL models, such as recursive neural networks, were applied to the dataset rather than learning automata so that it could be better analysed. The contrast between recursive neural networks (RNN) and neural backpropagation (NB) approaches is also used. The primary contribution made by the RDSA framework is to collect geo-location based information from nodes that are connected in a cloud-based system. This information is then subjected to sentiment analysis in order to extract the comment's sentiment, which can be a positive or negative response depending on how the analysis is performed. The user has provided a recommendation on a certain item based on the answer that was obtained from the sentiment analysis. The experimental assessment was carried out utilising Naive Bayes and RNN classifier for sentiment analysis using data sets from Amazon. These data sets included reviews on a variety of products, such as movies and foods. According to the findings of the test, the performance accuracy may reach up to 90.47 on movie reviews and 90.34 on food item ratings, respectively.

Researchers came up with the idea for a sentiment analysis-based recommender system in 2016 [20]. This system would use sentiment analysis to rate products. This approach gives more accurate results by comparing retrieved tweets from Twitter using a variety of classification algorithms, such as NB and SVM. The implementation of a dual prediction strategy as well as an SVM text classifier is the primary contribution of this method. The experimental assessment was carried out using data from Twitter, and it delivers performance accuracy of up to 82%.

A sentiment analysis-based recommender system was developed [21]. This system is intended to enhance recommendations by drawing trust and emotion inferences from online social networks. A framework for an implicit social trust and sentiment-based recommender system is presented in this study. This approach was validated via the use of experiments using real-time social data obtained from Twitter. This recommender system makes use of machine learning techniques such as neural networks, logistic regression (LR), and DTs. The use of online social networks as a new source of data is the primary contribution that this implicit social trust and sentiment based recommender system makes to the field. Utilize users' tweets as "micro reviews" in the implicit social trust sentiment-based recommendation system that you have developed. By using sentiment analysis, the author is able to get different score evaluations from the postings made by friends in microblogging. Offers a trustworthy component in the form of communication between friends and boosts performance via the use of a variety of machine learning classification methods. Using tweets from the Twitter API that were connected to the movie domain, an experimental assessment of the strategy was carried out using several machine learning approaches such as NB, LR, and DT. According to the findings of the assessment, the level of performance accuracy achieved was 57.65% for NB, 76.6% for LR, and 72% for DT.

Researchers suggested a recommender system that takes into account the thoughts or feelings of users with relation to the services offered by online shopping websites [22]. They made use of a stochastic learning system in order to categorise the feelings that were reported by the user. By using the MAC address of the machine, this recommender system will discover any fraudulent evaluations and will not let their publication. The most important addition that this framework has made is the installation of stochastic learning and a context-based engine. These features were included with the goal of improving performance and overcoming the limitations of classic recommender systems.

3. METHOD

This section presents GLCM texture feature extraction and CNN enabled optimized model for sentiment analysis as shown in Figure 1. In this model, tweets are given as input. Firstly, GLCM algorithm is used to extract texture features from the input data set. This feature extraction helps in achieving higher classification accuracy. Classification is performed using CNN. It achieves higher accuracy than the SVM and AdaBoost algorithm.

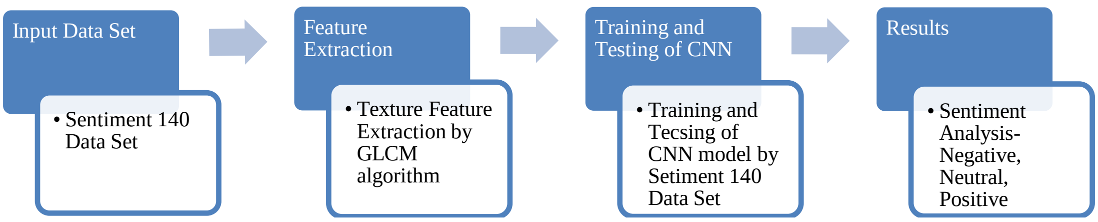

Figure 1.GLCM-CNN model for sentiment analysis

Every classification approach makes use of a method known as feature extraction in order to filter out unnecessary information from the training set. It is necessary to conduct an evaluation of the extracted features for qualities such as sparseness, dispersal, overlap, presence of outliers, Gaussianity, non-Gaussianity, linearity, and non-linearity in order to determine which classifiers are the most effective for a specific classification problem. This evaluation must be carried out before it is possible to determine which classifiers are the most effective. Up until then, there is no way for us to determine which classification methods are the most precise.

The GLCM is a tool that may be used to gather statistical information from photographs on the texture of any order [23]. This matrix is a representation of the frequency with which each grey level is positioned in close proximity to every other grey level. The number of rows and columns in a GLCM matrix is equal to the number of different tones of grey that are present in an image, also known as pixels. It has been demonstrated that the core component of this method, which is a two-dimensional histogram plot of grey levels for a pixel pair with a known spatial link, is simple to put into practise and is effective at classifying the underlying textures of images. The retrieved textural characteristics of the GLCM can be used to gain insight into the complexities of the overall content of the picture. There is a possibility that the GLCM-derived feature vectors for medical imaging may differentiate between healthy and unhealthy states. The GLCM offers a statistical analysis of the texture that is sensitive to the dynamic relationship that exists between the pixel locations in space.

When applied to big datasets, the efficacy of machine learning algorithms is substantially reduced due to challenges such as underfitting, model complexity, and a lack of resource efficiency. The inefficiencies caused by these challenges reduce the effectiveness of the approaches. DL networks make it possible to sift through vast amounts of data in search of previously undiscovered insights, to make predictions about the future based on this newly acquired information, and to put this newly acquired information to use in real-world situations. Computer models are now able to learn from both graphical and textual data thanks to the use of "deep learning." As the amount and diversity of data that is available has increased, several DL architectures have been developed in order to attain amazing performance in comparison to more conventional machine learning methods.

When it comes to computer vision (CNN), the CNN is one of the types of deep neural network architecture that is considered to be among the most popular [24]. A CNN is made up of several different layers, the most important of which are the convolutional layers, followed by the pooling layers, the activation layers, and the connected convolutional layers. To complete tasks from the beginning to the very end, a deep CNN uses multiple convolutional layers that are connected to one another. Filtering is the primary role that the convolutional layer plays in the neural network. Only a very small portion of the pixels that make up the input image (let's say, 3×3) are passed through the filter that is located in the convolutional layer. CNN model is presented in Figure 2.

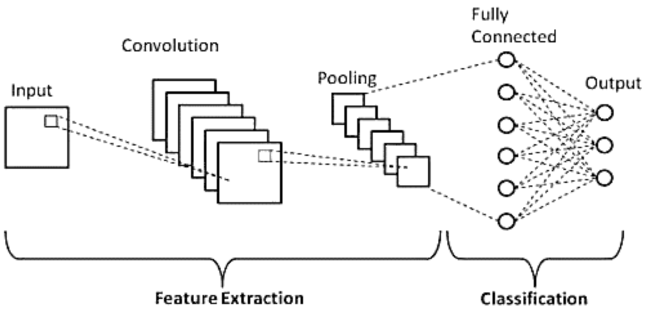

Figure 2. CNN

The pixel values go through a "dot" operation, and the filter makes use of a weight to determine how much of an impact this has on the output in the end. After the convolutional layer has been applied to the image, the size of the data point matrices in the image is decreased. The matrix in the activation layer is what gives the network its nonlinearity, and back propagation is used to train the network using the input matrices from the activation layer. When multiple samples are combined into one, the number of layers in the filter matrix is diminished, which in turn causes the matrix to take up less space. A layer is considered to be a max layer if it selects the highest possible value for each category's corresponding attribute. The output of the max layers is used by the linked layer to generate a probability distribution that is applied to all of the possible labels. For the purpose of calculating these probabilities, the connected layer is utilized. The likelihood of a label accurately predicting the result is taken into consideration when selecting a label [25].

4. RESULTS AND DISCUSSION

The sentiment 140 data set [26] is utilised for experimental purposes. The dataset comprises 1,600,000 tweets that were extracted using the Twitter API. The tweets have been labelled with a scale ranging from 0 (negative) to 4 (positive), enabling the detection of sentiment. A total of 2,000 occurrences were chosen from the dataset for this experiment. The model was trained using 1,600 instances, tested using 200 instances, and validated using the remaining 200 instances.

When judging performance, the most important things to look at are classification accuracy, precision, recall, and F1 score. When trying to explain how well the models did based on the test data, a method called a "confusion matrix" is often used to show the results. With the help of the confusion matrix, you can see how well the techniques for machine learning work. The confusion matrix can figure out four different numbers: true positive (TP), false negative (FN), true negative (TN), and false positive (FP). The term "true positive" means that the model has decided that a certain amount of information is positive, and that information itself is positive. "TN" means that all of the data that has been put into a category is negative and has been marked as such.

A FP is also the number of data points that have been marked as positive even though they have a negative value. A "false positive" is also sometimes called a "type 1 mistake." In conclusion, the FN is a way to show that the data quantity is negative and is classified as negative. The FN is a type of mistake that is also called type 2. These variables can be used to figure out the classification accuracy, precision, recall, and F1 score of deep CNNs, as well as those of current machine learning and transfer learning methods. Performance is compared on the basis of following parameters.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

$$Sensitivity = TP/(TP + FN)$$

$$Specificity = TN/(TN + FP)$$

$$Precision = TP/(TP + FP)$$

Results are shown in Figures 3-6. Texture characteristics are extracted from the input data set using the GLCM technique. This feature extraction improves categorization accuracy. CNNs are used to classify objects. It outperforms both the SVM and the AdaBoost algorithms in terms of accuracy. CNN has achieved an accuracy of 98.5% for sentiment analysis task.

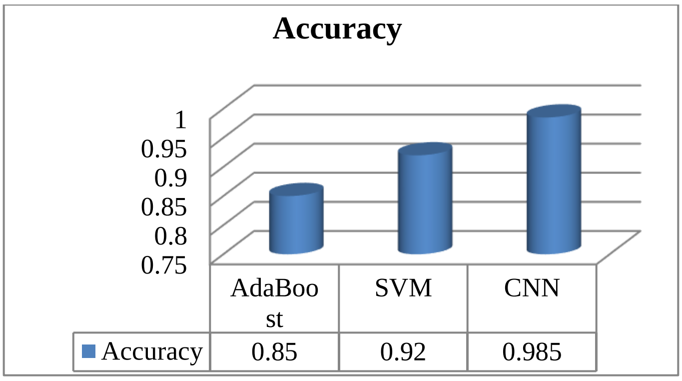

Figure 3. Accuracy of classifiers for sentiment analysis of social media data

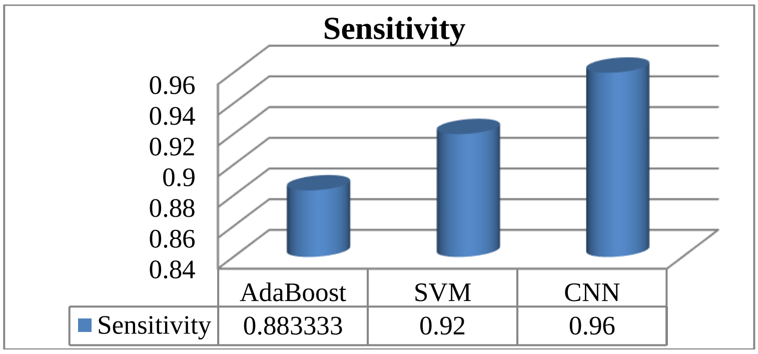

Figure 4. Sensitivity of classifiers for sentiment analysis of social media data

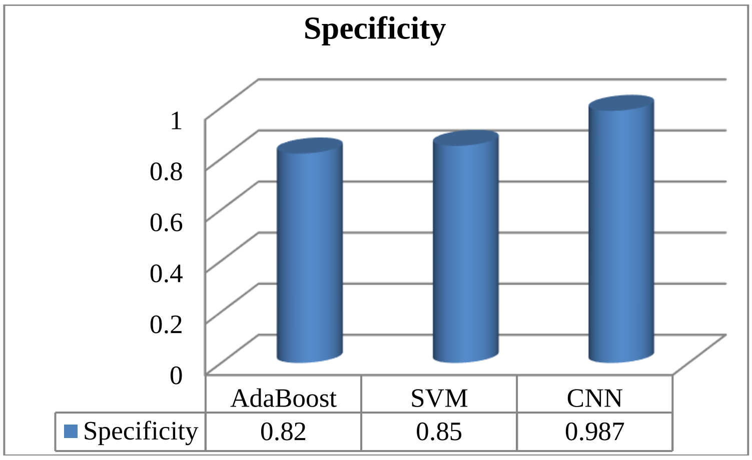

Figure 5. Specificity of classifiers for sentiment analysis of social media data

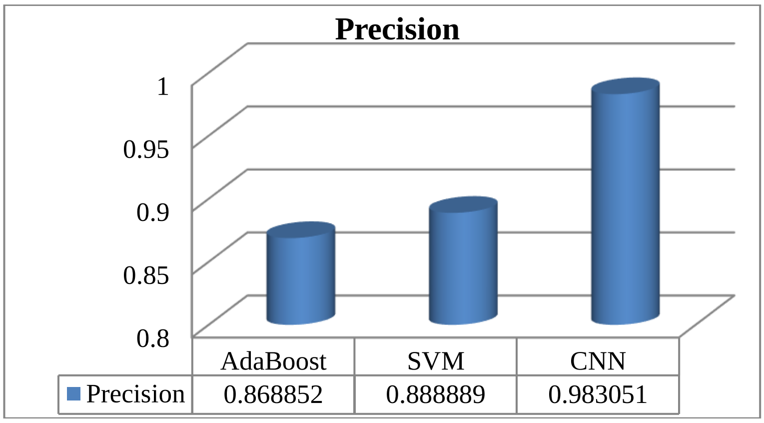

Figure 6. Precision of classifiers for sentiment analysis of social media data

5. CONCLUSION

It has been suggested that applications for sentiment analysis and mining social media content have played a role in the recent successes of both private industry and the government. Emotion analysis has a wide variety of potential applications in contemporary life, ranging from individuals to corporations, from the field of telecommunications to the field of medicine, and from the realm of economics to the field of politics. These fields include: a CNN and GLCM texture feature extraction-based model that is optimised for sentiment analysis is presented in this paper. Tweet data are used extensively in the construction of this model. In the first step of the process, texture features are extracted from the input data set using the GLCM approach. This approach of feature extraction results in an improvement in the classification precision. The CNN is used in order to accomplish the classification jobs. It outperforms the SVM method as well as the AdaBoost algorithm when it comes to precision.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Chinta Veena	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Kavita A. Sultanpure		✓				✓		✓	✓	✓	✓	✓		
Meenakshi	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Sunil L. Bangare	✓	✓		✓		✓		✓	✓	✓			✓	
Punam Sunil Raskar		✓				✓		✓	✓	✓	✓	✓		
Shriram Sadashiv Kulkarni	✓	✓	✓	✓		✓	✓			✓	✓		✓	✓
Myla M. Arcinas	✓		✓	✓	✓	✓		✓	✓	✓			✓	
Kantilal Pitambar Rane	✓		✓	✓	✓	✓			✓		✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review &**E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are openly available in [https://www.kaggle.com/datasets/kazanova/sentiment140] at reference number [26].

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BIOGRAPHIES OF AUTHORS

Dr. Chinta Veena is working as an Associate Professor in Computer Science and Engineering (AI) Department, G.Pullaiah College of Engineering and Technology. She has completed M.Tech. in Computer Science and Engineering from JNTU Anantapur in 2013. She completed Ph.D. (CS) in Rayalaseema University, Kurnool. She is having a total 12 years of teaching experience. Her research area of interest are cloud computing, network security, and data mining. She can be contacted at email: cveena30@gmail.com.

Dr. Kavita A. Sultanpure working as an Associate Professor in the Department of Information Technology at Vishwakarma Institute of Technology, Pune, India. She graduated in Bachelor of Engineering in Computer Engineering from Cummins College of Engineering at SPPU, Pune, Maharashtra, India. She secured Master of Engineering in Computer Engineering at Pune Institute of Computer Technology at SPPU, Pune, India. She completed Ph.D. in the field of Computer Science & Engineering at KoneruLakshmaiah Education Foundation (K. L. University), Vaddeswaram, India. She is in teaching profession for more than 20 years. She can be contacted at email: kavita.sultanpure@gmail.com.

Dr. Meenakshi is an expert in Media and International Relations, Intercultural Communication, Event Management, Radio and TV Journalism and has a background in Continental Philosophy. She has taught these subjects for nearly 11 years at universities such as the Kurukshetra University (Haryana, India), LLDIMS, GGSIP University (Delhi, India), Lovely Professional University (Punjab, India), GD Goenka University (India) and at Apeejay University, India. She can be contacted at email: mt6458@gmail.com.

Dr. Sunil L. Bangare working as an Associate Professor in the Department of Information Technology at Sinhgad Academy of Engineering, Pune, India. He graduated in Bachelor of Engineering in Electronics and Telecommunication at Amravati University (SGBAU), Amravati, Maharashtra, India. He secured Master of Technology in Information Technology at Bharati Vidyapeeth Deemed University, Pune, India. He completed Ph.D. in the field of Computer Science & Engineering at Koneru Lakshmaiah Education Foundation (K. L. University), Vaddeswaram, India. He completed his PGD C-DAC. He is a Fellow (FIE)-The Institution of Engineers (India). He is in teaching profession for more than 16 years and have 1.6 years of industrial experience. He can be contacted at email: sunil.bangare@gmail.com.

Dr. Punam Sunil Raskar received B.E. degree in Electronics & Telecommunication Engineering from Savitribai Phule Pune University, Pune, India in 2011 and M.E. degree in Electronics and Telecommunication Engineering (VLSI and ESD) from Savitribai Phule Pune University, Pune, India in 2013. She is Gold Medalist in VLSI & ESD stream 2013 batch in SPPU. She has competed her Ph.D. Pune in Department of Electronics and Telecommunication Engineering in 2022. Her current research interest are belongs to image/video processing, image/video forensics, machine learning, and deep learning. She can be contacted at email: punamraskar4@gmail.com.

Dr. Shriram Sadashiv Kulkarni is working as Associate Professor and Head of Information Technology Department of Sinhgad Academy of Engineering, Pune, India. He has done his Ph.D. in Electronics and Telecommunication from Sinhgad College of Engineering, affiliated with Savitribai Phule Pune University in 2021. He received M.E. in Electronics and Telecommunication from Government College of Engineering, Pune in 2004. His areas of research are wireless communication, signal, and image processing. He can be contacted at email: kulk.shri@gmail.com.

Dr. Myla M. Arcinas is an associate professor of the Behavioral Sciences Department of De La Salle University and an SDRC research fellow. She does research on gender, overseas Filipino workers and their left-behind family members, and health. She obtained her Ph.D. in Sociology from DLSU-Manila. She can be contacted at email: myla.arcinas@dlsu.edu.ph.

Dr. Kantilal Pitambar Rane received B.E degree in Electronics and Telecommunication Engineering from North Maharashtra University, Jalgaon in 1996. M.E Degree in Electronics Engineering from Shivaji University, Kolhapur in 2005. Ph.D. Degree in Electronics Engineering from North Maharashtra University, Jalgaon in 2013. He is currently working as Professor at Bharati Vidyapeeth College of Engineering Navi Mumbai, India. His research interests include image processing, IoT, AI, and machine learning. He can be contacted at email: kantiprane@rediffmail.com.