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An Innovative Method for Election Prediction using Hybrid A-BiCNN-RNN Approach

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***Abstract* –Sentiment, volumetric, and social network analyses, as well as other methods, are examined for their ability to predict key outcomes using data collected from social media. Different points of view are essential for making significant discoveries. Social media have been used by individuals all over the world to communicate and share ideas for decades. Sentiment analysis, often known as opinion mining, is a technique used to glean insights about how the public feels and thinks. By gauging how people feel about a candidate on social media, they can utilize sentiment analysis to predict who will win an upcoming election. There are three main steps in the proposed approach, and they are preprocessing, feature extraction, and model training. Negation handling often requires preprocessing. Natural Language Processing makes use of feature extraction. Following the feature selection process, the models are trained using BiCNN-RNN. The proposed method is superior to the widely used BiCNN and RNN methods.**

***Keywords*—Convolutional Neural Network (CNN), Election prediction, Natural Language Processing (NLP).**

I. INTRODUCTION

People all across the world now turn to social media to voice their opinions on everything from a new product to an important news story. Opinion mining, often known as sentiment analysis, is largely concerned with the study of public opinion. Sentiment analysis is a subfield of natural language processing used to ascertain the author's intended meaning in a passage. The polarity of textual data is established by identifying the presence or absence of positive, negative, or neutral sentiments. Sentiment analysis can be performed on multiple levels, from the individual word to the entire document, from a single element to the entire concept. Phrase-level, and document-level, and word-level sentiment analysis all return positive results for the presented content is analyzed to assess the overall mood conveyed by the words, sentences, and piece of writing. Aspect-level sentiment analysis dissects broad topics into their constituent parts product analysis, and object analysis. Objects of study are selected, and a general consensus on how individuals feel about them is gleaned. Sentiment analysis at the concept level focuses on evaluating emotional language. Similar meaning texts are grouped together as related concept. Predicting the results of U.S. presidential elections has been big business for political scientists and observers for decades originated in Western Europe, specifically the United Kingdom. This forecasting election results, most notably in spanning decades in democratic nations, raises the how realistic global election simulations are how precise a forecast may be, and how much progress can be ways in which the present election forecasts could be improved, The consolidation of information from several sources administrative frameworks. Academics in this area of system results on the project's viability were very diverse. Academic research on elections may be broken down into people like theorists, aggregators, and formalists the power of analysis and judgment. Structuralism is a method used by macroeconomic indicators and variables to determine the Incumbent's Proportional Vote Share nominee of that party and/or that person's predicted share of the vote. The widespread use of social media platforms for communication, social participation, and self-expression makes it possible to easily and unobtrusively collect people's ideas thanks to the profusion of willingly offered personal information online. When compared to traditional methods of gathering and analyzing data on public opinion, social media sites provide a more rapid and less time-consuming alternative. Scholars that utilize social media data to measure public opinion claim that the predictive value of social media analysis does not depend on how representative the users are of the larger community. The popularity of the microblogging service Twitter has led to it being explored extensively. Over 100 million people use Twitter on a daily basis, and there are approximately 331 million monthly users. As such, it facilitates free expression, open dialogue, and global community building. Multiple studies have identified correlations between Twitter use and societal or electoral outcomes including voter turnout and opinion poll results. However, some have cast doubt on the validity of these studies and on the possibility of replicating their results. About a quarter of all adult internet users in the United States took involved in political campaigns via social media during the midterm elections. This share is only going up, thus researchers are working hard to make sense of all the data being produced by different channels. It has been reported that the volume of Twitter conversation can be used to foretell outcomes such as the outcome of the German elections or the success of a new film. Considering the gap between likely voters and social media users, the latter conclusion stands out; it's plausible that the observed pattern was an anomaly. Here, the proposed approach test the predictive power of Twitter data by applying it to a number of contests from the most recent US Congressional elections. Our key discovery is that such predictions have never done better than chance up to this point the limits of utilizing social media data to predict elections.

II. LITERATURE SURVEY

The aforementioned data warehouses have been used by numerous political campaigns to better understand voter preferences and tendencies. Politicians' heavy spending on social media campaigns right before elections, as well as the heated debates and arguments between their supporters and opponents, lend credence to the idea that user-posted content might sway election outcomes [1].Although the studies all recommended slightly different approaches, Twitter data was always identified as the most trustworthy and valuable resource citation [2]. A Twitter-based prediction framework, such as the one described, consists mostly of data conditioning and predictive analysis phase [3].Then, the proposed approach compare the SVM forecast to marketplaces (IEM) in the state of Iowa. There were a total of 40 million tweets collected for examination. Utilizing the SVM Future View The results have a high positive connection with the IEM and point to Obama's victory in the election vote, suggesting that Twitter may be trusted as a resource for understanding how voters feel about the U.S. presidential election. Conclusions of the vote [4]. The 2016 U.S. presidential election was used as an example. Twitter is where the proposed approach found all this information. The goal of the Twitter data mining was not to forecast the outcome of the election result, but rather to provide a comprehensive analysis of online tweets. They throw parties, Personality and policy ramifications of a major declaration of candidature [5]focused extensively on the presidential election of 2016.With the proliferation of social media as a platform for interpersonal interaction, group activity, and individual expression, people have become increasingly comfortable disclosing their personal information online. Thanks to the openness of social media, researchers may now collect an accurate cross-section of the population's opinions and attitudes [6]. Internet-based social networking sites' meteoric ascent has provided individuals with fresh opportunities for interpersonal connection, political participation, and self-expression. By sharing and discussing media like podcasts, videos, and articles members of these online communities help each other keep up-to-date and connected. Social networking services such as LinkedIn,Facebook,Myspace,Friends Feed, and many more [7] are seeing tremendous development, while Twitter has a much higher amount of tweets.The popularity of social media platforms like Twitter, Facebook, and Instagram can be attributed to the fact that users have a platform to voice their thoughts and ideas on any number of issues. Supporters of many political parties use social media to spread their views ahead of elections. This system focuses on the Pakistani general election. The proposed approach found that Punjab province was a strong test case for the predictive capacity of social media due to its population and people's tendency towards using it. Unfortunately, the platform's utility was significantly reduced in Baluchistan[8].Computing emotion and perspective assessment is a growing field of study. That's why it's possible to use data from social media platforms for electoral prediction. Predicting public opinion and conducting market research based on social media activity can yield reliable results [9].In recent years, social media's popularity has surged. To determine which parties in Pakistan's 2013 general election were the most well-liked, researchers employed a keyword-based collection of tweets that zoomed in on political party names and political personalities [10].The fields of opinion mining and sentiment analysis have flourished in tandem with the proliferation of new tools designed to process and analyze subjective data.[11] In recent years, scholars have developed sentiment analysis methods that can be used in a wide range of contexts, from election outcome forecasting to disease surveillance to analysis of stock market data to the assessment of consumer feedback.[12] This method focused mostly on the use of social media data for election prediction. The number of Indians who use social media has exploded in recent years, spawning a complex ecosystem [13] that spans fields as varied as politics, news, government policy, economics, and health. Voters in today's elections frequently utilize social media to discuss candidates, issues, and political parties. Predictive value of Twitter data in elections was regularly shown to be promising in early research. The authors revealed promising findings regarding the use of social media in predicting election outcomes across countries [14].The two most important aspects in enhancing prediction are the quality of the data and the methods employed to get it [15]. Inaccurate results may be produced if the information gathered isn't very relevant to the situation. Voting is a cornerstone of our democratic system. It's the cornerstone of democratic engagement between citizens and their government. Election outcomes have always been highly scrutinized due to their effect on the ruling body. It's the main way regular people communicate with their government. The election poll or survey plays a vital role in the democratic system. The first modern-style opinion poll was conducted in the early 19th century [16]. Several credible statistical models exist today that can accurately forecast the outcome of an election, as shown in [17]. It has lately come to light that the results of traditional polls may not be trustworthy. To improve their election forecasting, scientists are increasingly looking to digital data like blog posts and user behavior on social networks. [18] In addition, unlike traditional polls, online information is easily accessible and affordable to obtain. Politics and the meteoric rise of social media both present fascinating research opportunities. It's fascinating to see how technology is being used to solve modern problems. Many positive, negative, and ambivalent opinions [19] can be found online and in real life regarding the Presidential and Vice Presidential candidates in Indonesia. In a true democracy, both the members of parliament and the president are chosen by the people. Each political group has its own media infrastructure to promote its candidates [20]. Politicians and other public figures routinely utilize social media to promote themselves and increase their profile in the run-up to midterm and general elections. People's perspectives can be heard on all sorts of issues in today's social media climate ranging from social and political issues to commercial products and services [21]. As of the now, Twitter is the most popular microblogging site out there opinion mining from weblog posts. Politics, current events, and other timely topics are often discussed by Twitter users. The need for technologies that can help make sense of the public's tweets regarding the presidential contenders is growing.

III. PROPOSED SYSTEM

Because they house a vast lot of people's thoughts about politics and leaders, social media platforms like Face book and Twitter can be used by researchers as a source of information for many tasks, including election prediction. Identify, categorize, investigate, and summarize the Twitter resources used for election prediction. They conducted a systematic mapping study (SMS) and provided supporting empirical data to investigate Twitter's use for election prediction between January 2010 and January 2021.

A. Preprocessing:

A regular expression is used to identify the presence of a URL, and if one is found, the corresponding portion of the received tweet is removed. All "@username" accounts are then removed. Then it removes any punctuation or hashtags that are marked with a "#" symbol. After tweets are filtered, they are classified into one of several groups.
The effectiveness of our classifier is greatly bolstered by its capacity to deal with negation. The most challenging aspect of sentiment analysis is determining how to handle unfavorable comments. By parsing the sentence "not win," they discover that the word "win" has a profound effect on our disposition. As a result, misclassifications will always occur. The omission of "not" is the root of this error. They used a straightforward approach involving state variables and bootstrapping to deal with negations to overcome this issue. Separate notation for negative shapes was an idea developed in this system [22]. A variable is used to keep track of the negation status in this approach. If a word follows the lettersn't or not, it will be written as "not "+word. All processed text is interpreted as "not"+word when the negation state variable is present. If a period or double negation is found, the state variable will be cleared. Several highly charged phrases are only represented in the training set by their standard forms. However, their polar opposites would be extremely forceful. They solved this issue by experimenting with illustrative and inverse instances of the target category. During training, the number of instances of "fail" in the negative class is increased by one whenever the word comes in a negative document, while the number of instances of "not fail" in the positive class is decreased by one. This is done to ensure that there are enough "not" forms for processing and organizing data. Classification accuracy was much enhanced when trained using bootstrapped negated forms.

B. Feature Extraction:

In Natural Language Processing (NLP), the TF-IDF approach is commonly used to extract high-quality words and their scores from a given corpus. A word's TF value is an indication of how often it appears in the corpus. Another important indicator of a word's importance is its document frequency (DF), which is the percentage of papers that contain that term. The multiplicative inverse of DF (IDF) also provides a measure of the frequency with which individual words occur in a text. The frequency term $tf(u,\varphi)$ is given by Equation (1):

$$tf(u,\varphi) = \frac{b_\varphi(u)}{max_{y\in e} b_\varphi(y)} \tag{1}$$

Where $b_\varphi(u)$ is the frequency of the term u in document and $b_\varphi(y)$ is the total number of words in document φ. Similarly, Equation (2) can be used to represent the IDF of the u th word:

$$u\,df(u,\Delta) = ln\left(\frac{|\Delta|}{|\beta|}\right) \tag{2}$$

$$\beta = \varphi \in \Delta : u \in \varphi$$

Where Δ represents the entire number of documents and β denotes the papers containing the u -th sentence. The TF-IDF may not always be the most effective strategy for extracting feelings and attitudes from data. Using sarcasm with the frequency score could be problematic. It's okay if you don't like me; I don't have the energy to pretend to be your friend if you don't have decent taste. In both cases, TF-IDF may incorrectly interpret the intended tone of the text [23]. Bigrams and trigrams are often used in text processing to form links between nearby words for enhanced comprehension. The probability of a word wk given all preceding words $T(y_h|y_{1:h-1})$is modeled in the bigram model, however only the word immediately before it is taken into account $T(y_h|h-1)$ The following formula derives the likelihood of a word sequence from the bigram probabilities of its constituent words.

$$T(y_{1:h}) = \prod_{H=1}^{g} T(y_u|y_u - 1) \tag{3}$$

As shown in (4), normalized counts from the corpus can be used to construct bigram scores with TF-IDF scores.

$$T(y_u|y_{u-1}) = \frac{J(y_{u-1}y_u)}{\sum_y J(y_{u-1}y)} \tag{4}$$

C. Model Training:

1) CNN:

In natural language processing, local features are extracted using CNNs with several convolution layers. These networks employ convolutional linear filters to process the input attributes. To apply a CNN to a sentence S with s words, the proposed approach need an embedding vector of size e, where e is the number of words in S. The input feature matrix M is used as a filter for submatrix applications of size $e \times k$. The finished feature map appears as seen above. If $L = [l_0, l_1, \ldots, l_{a-k}]$, then the following holds true.

$$l_u = B.A_{u:u+k-1} \tag{5}$$

Where $A_{u:c}$ is a row- u to row- u submatrix of A and $u = 0,1,\ldots,a-k$. It is common practice to input feature maps into a pooling or sub-sample layer in order to reduce their dimensionality. One frequent pooling approach, called "max-pooling," works like this to pick out the most crucial feature f in the feature map:

$$f = \max_{0 \le u \le a-k} \{l_u\} \tag{6}$$

A pooled feature vector is created by concatenating the outputs of a pooling layer, and this vector can be fed into a fully connected network.

2) BiCNN-RNN:

The system presents a new deep model, ABCDM, that allows for the recognition of polarity in both short and long user comments. The drawbacks of earlier deep architectures for sentiment analysis are addressed by this new deep model, ABCDM. ABCDM uses a CNN, bidirectional LSTMs, bidirectional GRUs, GloVe word embeddings, an attention mechanism, and bidirectional LSTMs to better capture local features and long-term relationships. In order to build the input comment matrix, a comment vector $j \in \mathbb{R}^l$ is first embedded into a pre-trained GloVe embedding matrix $y_n \in \mathbb{R}^{g \times d}$, where g is the total number of words and d is the embedding dimension, and m is the padding length or the maximum amount of words $y_p, p \in [1, l]$ considered in the remark.

$$j_p = Y_n y_p, p \in [1, l] \tag{7}$$

The output of the embedding layer is then sent into two concurrent layers of Bi-LSTM and Bi-GRU, which process sequences of arbitrary length and extract lengthy dependencies in both directions. The suggested model can now remember both short and extended sequences thanks to the use of GRU and LSTM.

$$\vec{k}_{p\ LSTM} = \overrightarrow{LSTM}(j_p), p \in [1, l] \tag{8}$$

$$\overleftarrow{k}_{p\ LSTM} = \overleftarrow{LSTM}(j_p), p \in [l, m] \tag{9}$$

$$\vec{k}_{p\ GRU} = \overrightarrow{GRU}(j_p), p \in [1, l] \tag{10}$$

$$\overleftarrow{k}_{p\ GRU} = \overleftarrow{GRU}(j_p), p \in [l, m] \tag{11}$$

By joining the foreground and background contexts of a word, y_p, they can now acquire an annotation.

$$k_{p\ LSTM} = [\vec{k}_{p\ LSTM}, \overleftarrow{k}_{p\ LSTM}] \tag{12}$$

$$k_{p\ GRU} = [\vec{k}_{p\ GRU}, \overleftarrow{k}_{p\ GRU}] \tag{13}$$

The attention mechanism is used to $k_{p_{LSTM}}$ and $k_{p_{GRU}}$ so that the model can give more or less importance to individual words in the comment. They did this by making a few adjustments to the feature vector, which involved pulling out some key terms from the comment.

$$k_{p_{LSTM}} = \tan k\left(Y_{y_{LSTM}} k_{p_{LSTM}} + f_{y_{LSTM}}\right) \tag{14}$$

$$k_{p_{GRU}} = \tan k\left(Y_{y_{GRU}} k_{p_{GRU}} + f_{y_{GRU}}\right) \tag{15}$$

$$\varepsilon_{p_{LSTM}} = \frac{exp\left(i^P_{p_{LSTM}} i_{y_{LSTM}}\right)}{\sum_p exp\left(i^P_{p_{LSTM}} i_{y_{LSTM}}\right)} \tag{16}$$

$$\varepsilon_{p_{GRU}} = \frac{exp\left(i^P_{p_{GRU}} i_{y_{GRU}}\right)}{\sum_p exp\left(i^P_{p_{GRU}} i_{y_{GRU}}\right)} \tag{17}$$

$$A_{LSTM} = \sum_p \varepsilon_{p_{LSTM}} k_{p_{LSTM}} \tag{18}$$

$$A_{GRU} = \sum_p \varepsilon_{p_{GRU}} k_{p_{GRU}} \tag{19}$$

Where i_p is an untransparent representation of k_p, and k_p is a context vector that is initially randomly seeded and learns together with i_y throughout training. Similarity between two words can be utilized to determine their relative importance using Eqs. (16) and (17). The final s value is calculated by summing the individual weights of significance.

The comment vector, denoted by ε_y . a ,compiles information from the comment's words into a single space-separated string. In order to find meaningful local features and minimize the input data dimension, a convolution operation is done to the final comment representations. Using convolution, the model can also be made position-independent. Each of the ABCDM model's two branches the Bi-LSTM and the Bi-GRU has its own parallel convolution layer with a unique kernel size [24]. Here, convolution in only one dimension is carried out. In particular, two 1D-CNN with a fixed number of filters and a variable window size are applied independently to the comment representation (i.e., the outputs of Bi-LSTM and Bi-GRU units), as shown in Eq. (20).

They obtain four outputs from the CNN layer by running two different CNNs on the outputs of the Bi-LSTM and Bi-GRU layers. Using maximum and average pooling layers stacked on top of one another, CNNs down sample their feature maps. The feature relocation results in less distortion in the resulting feature maps. $M_{j_u} = [m_{j_1}, m_{j_2}, \ldots, m_{j_b}]$ $u \in [1,6]$ At the end of each pooling, they get the final feature vector M_j, where b is the total number of filters in the CNN layer. They created 8 unique regional feature maps by separately applying maximum and average pooling to each CNN.

At last, the document vector is built by joining together all of the feature vectors. Therefore, $M_j = [m_{j_1}, m_{j_2}, \ldots, m_{j_8}]$. Batch normalization was used to speed up network training and reduce the likelihood of overfitting after the M_j vector was obtained. The polarity of future comments is predicted by transforming a M_j vector into a fully connected dense layer representation. The following expression is used to calculate the output of this layer.

$$k_e = Relu(Y_e k_t + f_e) \tag{20}$$

Training yields the parameters Y_e and f_e, and the union of pooling layers by batch normalization yields the hidden representation k_t. In the end, the dense layer's output is sent into a sigmoid-function output layer for binary classification.

IV. Result and Discussion

In order to gauge public opinion, elections are held in which individuals cast ballots for their preferred candidate. In order to foretell the outcome of an election, numerous organizations and media outlets undertake pre-poll surveys and solicit the opinions of experts. In order to foretell the results of an election, they collect and analyze tweets concerning the candidates in question.

TABLE I. Comparison of the Models.

MODEL	Accuracy	Precision	Recall
RNN	90.63	89.62	88.47
BiCNN	94.12	93.48	92.38
BiCNN-RNN	98.34	97.61	96.54

The table I demonstrates that BiCNN-RNN achieves a 98.34% accuracy, while CNN achieves a 94.12% accuracy.

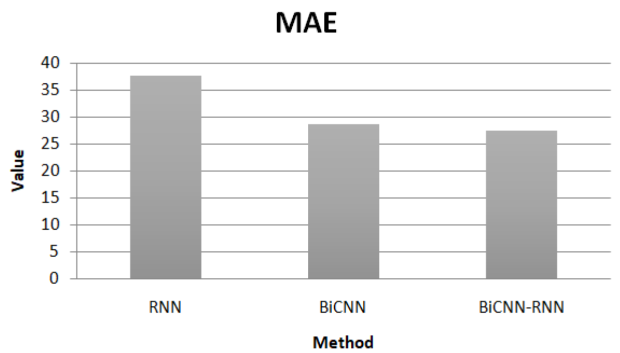

Fig. 1. The MAE Comparision among different methods

Evaluation indices based on expected value and actual value were used to compare the three methods, and the results are shown in Figure 1.

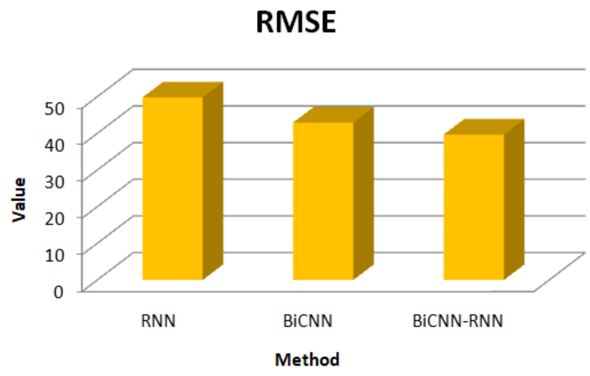

Fig. 2. The RMSE Comparision among different methods

The evaluation index for each strategy is derived by comparing the predicted value to the actual value. The MAE and RMSE values in Figure 2 are both highest for MLP.

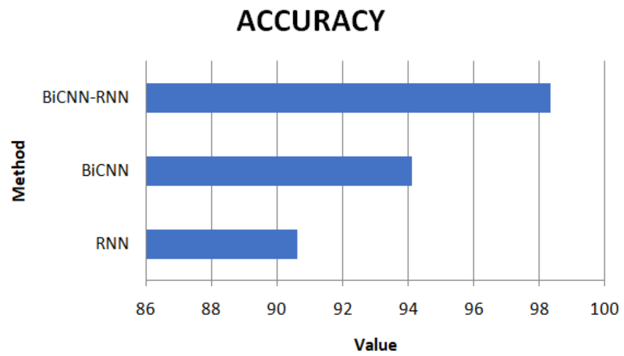

Fig. 3. The Accuracy Comparision among different methods

This result demonstrates the reliability of model comparisons. BiCNN-RNN-98.34% accuracy is achieved by our proposed model technique.

V. Conclusion

Since social media data are largely unstructured and created in real time, they have become a key focus in information retrieval (IR) and text mining. Whatever they write on the internet may be an expression of their innermost sentiments. The challenge of gleaning insights from social media data is a significant roadblock in the fields of data mining and knowledge discovery. Every election, people take to platforms like Twitter, Facebook, and Instagram to share their thoughts on the candidates, topics, and parties at stake. Negation handling often requires preprocessing. In the field of Natural Language Processing, or feature extraction plays an important role. The proposed method employs the BiCNN-RNN technique. The proposed method is contrasted with two well-known alternatives, the BiCNN and the RNN. The success rate of the recommended technique is roughly 98.34%, which is significantly higher than the other two.

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