Journal of Engineering Science and Technology
ICIST2024, Vol. 20, No. 5 (2025) 12 - 24

ADOPTION OF ADAM OPTIMIZER FOR ENHANCEMENT OF DEEP LEARNING MODEL IN POLITICAL SECURITY THREAT PREDICTION

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Abstract

Political security threats are the main challenges for governments and organizations around the globe and require the development of accurate predictive models for their proactive mitigation. Deep learning techniques have been successful in this area, but optimizing their performance is still a major challenge. Thus, this paper introduces a new way of strengthening deep learning frameworks for the prediction of political security threats by using the Adam optimizer. The Adam optimizer, famous for its efficiency in the optimization of deep neural networks, is used here to improve the predictive capabilities of the existing frameworks. Based on the findings of empirical studies on extensive datasets that cover different political circumstances and types of threats, we show that the proposed approach is effective in increasing the prediction accuracy and model convergence. Besides, the comparative studies with the traditional optimization methods confirm the superiority of the Adam optimizer in the improvement of the performance of deep learning frameworks for political security threat prediction tasks. This research is a step forward in the development of predictive analytics in the political security domains and it shows the importance of the optimization techniques in the improvement of the deep learning models that are used in the real world.

Keywords: ADAM optimizer, Deep learning, LST, Optimization,; Political threat.

1. Introduction

Today, cyberspace has proven to be a very powerful tool and can impact national security. As new risks emerge, there is interest in developing more advanced defence strategies [1]. The current response to this problem is too limited, as it cannot capture the scale of information sharing that big data analyses. In this cyber arena, various platforms become addresses for various types of transactions including emotional transactions among the public [1]. These feelings can trigger great security concerns, such as the real-world example at the beginning of the Arab Spring, where the spread of false information online exacerbated negative attitudes and led to social instability that endangered national security [1, 2]. The events of the Arab Spring are one round of examples showing how emotions affect social and political stability. People are emotional creatures, and the emotion of anger or fear can mobilize people towards collective action, even disruptive to society. For example, anger has been demonstrated to lead more often to approach behaviour (increasing social movement participation), while fear leads most frequently to avoidance [2]. Indeed, these emotional responses to political will unravel even relatively stable societies as seen in the Arab Spring protests. The collapse of stability in the Middle East and North Africa region caught almost all Western policy makers off guarded, but perhaps a paralytic counselling should be devoted to emotional matters within political and social regulation [3].

Emotions are known to have an important impact on human cognitive processes and decision-making [4]. Intelligence has been influenced by emotion, as they contribute for several underlying cognitive skills such as salience detection, decision making and adaptation in a critical way [4]. An interesting discovery is that non-compliant behaviour against security procedures can be influenced by emotions, with four main emotional traits in the field of information security domain including rage, trust fear and stress. Fear has been recognised as a foundational principle for keeping people using security measures. The emotion-based security threat detection is not meant to completely replace the traditional measures but can act as a complement strategy by providing an additional layer of intelligence and adaptability [5].

Recent research has pointed out that emotions detected with sentiment analysis, especially those emanating from social media, become highly important in the process of identifying potential security threats. The high-volume applications of sentiment analysis on user-generated content such as tweets or Facebook posts have proven useful in the monitoring of public sentiments indicative of social instability, disinformation dissemination, and other factors that can threaten national security [6]. Therefore, it may be said that emotional sentiment can act as an early warning signal for chaos, and the authorities can intervene at an early stage before tensions escalate, as in events like the Arab Spring [3, 7]. Advanced sentiment analysis harnessed the power of machine learning and AI technologies to identify not only emotional changes in content on social media but also predict possible security concerns. Using the methods of NLP, it can observe changes in emotional tone or intensity of the greater population and pinpoint problems such as anger, fear, or frustration that might be a larger threat to society [7].

Most of the platforms support various kinds of data exchange in cyberspace, including a broad range of public expression of emotions. Those might lead to security risks, as was demonstrated in events like the Arab Spring when negative sentiment fuelled through misinformation on the internet resulted in civil unrest that threatened national security. As such, promptly detecting disruptive sentiments like these is essential for authorities to effectively manage crises. However, existing methodologies for emotional evaluation regarding national security are inadequate [8]. While most researchers explore various techniques for classifying human emotions, there is insufficient attention given to connecting these emotions to security threats and developing appropriate measurement mechanisms. Despite the capability of sentiment analysis methods to ascertain word polarity, their application in predicting threats remains largely unexplored, particularly in the realm of political security [5, 8].

Our study aims to remedy this by enhancing the prediction of national security threats, with a specific focus on political security by developing an analytical model by leveraging the Adam optimizer with LSTM deep learning. Our proposed model will contribute to robust capabilities for assessing human emotions and their relationship with security threats. To validate our proposed model, an experimental analysis was conducted. The dataset for this research is constructed by collecting text data from various online platforms, and the proposed model seeks to open new research avenues at the intersection of sentiment analysis and national security. The model will achieve this to enhance emotion measurement and threat prediction in cyberspace.

2. Related Works

The next section presents the review of the studies on hybrid approaches that incorporate the lexicon-based method with machine learning, deep learning, and optimization techniques. These research studies will serve as a backbone in improving the model on political security. Sentiment analysis has become the main backbone of this study, where past research has used it as one of the most popular techniques in detecting threats in the online environment [9].

2.1. Hybrid lexicon-based approach and machine learning technique in political domain

Razali et al. [8] proposed a new theoretical framework to predict political security dangers within cyberspace. This newly proposed framework combines a lexicon-based approach with machine learning techniques. Threat classifiers include the Decision Tree, Naive Bayes, and Support Vector Machine algorithms in the presented framework. Experimental analysis was conducted in this paper to validate the efficacy of the framework. In fact, their findings showed that the hybrid approach, which merges the lexicon-based analysis with the Decision Tree classifier, was best for the prediction of political security threats. These findings contribute significantly to ongoing research in opinion mining for threat prediction and form a sound basis that encourages us to undertake any further investigation within this field of political security with due care and diligence.

2.2. Deep learning and optimization techniques

Deep learning is defined as an influential machine learning (ML) method that studies the properties of different layers or data to provide advanced predictive results [5] and is also a popular method of semi-supervised learning [10]. Optimization is defined as the practice of selecting the most favourable elements from a set of available alternatives. In its basic form, an optimization problem entails maximizing or minimizing a real function by selecting input values from a permissible set and evaluating the function's value based on those inputs [11].

Parveen et al. [12] introduce the Gated Attention Recurrent Network (GARN), which combines a recurrent neural network (RNN) with attention mechanisms to achieve efficient processing time, complexity, and accuracy in Twitter sentiment analysis. Previously existing literature had failed to achieve this due to the large size of Twitter's dataset. GARN resolves this by filtering out low-level and unwanted features, which not only reduced the efficiency of classifiers but also made up a large bulk of the dataset. Yaakub et al. [13] highlight the issue of datasets containing large amounts of low-level data, explaining that if this data is left unfiltered, it risks decreasing the accuracy of sentiment classification, thereby making it difficult to obtain an optimal subset of features.

Optimization algorithms, otherwise known as optimizers, are methods used to enhance the performance of deep learning models, as they can significantly impact the accuracy and efficiency of a model's training process. During this process, optimizers are responsible for iteratively adjusting the model's weights, while also minimizing the loss function at each epoch.

A comparative study by Bashetty et al. [14] discusses the various optimization techniques used in deep learning works. ADAGRAD, RMSPROP, ADAM, and YOGI are among the popular optimizers utilized, as they can be applied to evaluate and experiment with various datasets. The research by Paul et al. [15] introduces two deep neural network models based on Convolutional Neural Networks (CNN) and adopts an Adaptive Gradient Algorithm (ADAGRAD) optimizer to address the challenges posed by disaster scenarios. The first model aims to identify tweets relevant to disasters, while the second model focuses on extracting detailed information from these tweets, which can be valuable for various humanitarian activities. These models offer significant contributions to this field of research and the national security domain.

Table 1, which is based on reviewed publications, shows the current adaption of optimization techniques used in various domains. Here, we can see that optimization techniques are experiencing growth. This is due to advancements in algorithms, increased applications, integration with Artificial Intelligence (AI) and Machine Learning (ML), availability of big data and cloud computing resources, and industry demand for improved efficiency. With advancements such as these, new types of challenges will emerge, and so optimization methods will need to keep evolving to mitigate these obstacles.

Almu'iini Ahda et al. [16] demonstrated that the performance of the ADAM optimizer in addressing computational linguistics challenges in neural machine translation from Minangkabau to Indonesian was superior to that of the RMSProp optimizer.

Table 1. Optimization techniques in different domain.

Reference	Technique	Performance Metric
[16]	Computational Linguistics	Adaptive Moment Estimation (ADAM)
[17]	National Security	Adaptive Gradient Algorithm (AdaGrad)
[17]	Online Review/Business	Support Vector Regression With Sequential Minimal Optimization (SMO)
[17]	Computer Sciences	Bitwise Arithmetic Optimization Algorithm (BAOA)

3. Proposed Model

In our research, we developed the ADAM-LSTM Political Security Model to predict various threats from online platforms. Our model comprises of several key stages, including pre-processing, word embedding, threat detection, and parameter tuning. LSTM is used for threat detection, while the parameter tuning is based on the ADAM optimizer. Figure 1 illustrates the Workflow of ADAM-LSTM Political Security Model.

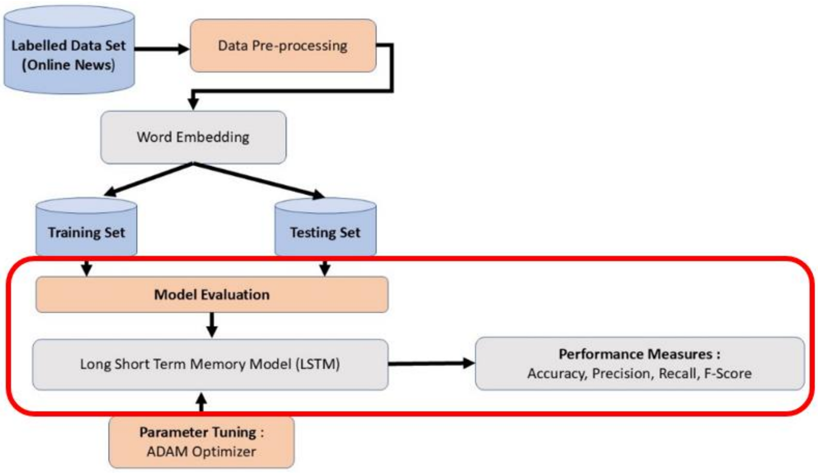

Fig. 1. Workflow of ADAM-LSTM political security model.

3.1. Dataset

In this experimental design, we used the labelled dataset provided by Razali et al. [8]. This dataset was originally created by manually gathering various Malaysian online news sources, such as The Star, New Straits Times (NST), and Free Malaysia Today (FMT), and more. The dataset comprises of 250 texts from online news sources. Out of these texts, 163 of them are categorized as positive, while the remaining 87 are categorized as negative. These positive and negative classifications serve as markers to ascertain the presence of threats within the sample texts.

3.2. Pre-processing

In Natural Language Processing (NLP), text pre-processing is a process that will enhance classifier performance and reduce feature complexity. In this process, unnecessary elements such as punctuation, HTML codes, and symbols are removed, and the gathered text data is then transformed to lowercase and normalized. The normalization process consists of two main steps. First, the unstructured text dataset is converted into a structured word vector, and then, the feature vector's dimensionality is reduced by eliminating unwanted words and stemming them to their original forms. Stemming refers to reducing words to their roots, while lemmatization is the act of utilizing a lexical knowledge base to convert words to their base forms by rooting verbs. At the end of the process, words will be encoded into numerical formats.

3.3. Word embedding

Word embedding is a technique used in NLP and deep learning to represent words as dense vectors of real numbers [18]. It is a way to map words to vectors in a continuous vector space, where similar words are represented by similar vectors. This experimental layer carries max_words as an input dimension, with 50 as the output dimension (embedding size), and max_len as the input length. This layer creates a low dimensional vector that deals with each word in the input sequences and directly replaces them with their dense vector representation. These vectors are then multiplied from the embedding layer container and are then sent to the LSTM layer for further processing.

3.4. Threat prediction using LSTM (long short-term memory)

Sufi [19] developed a global cyber-threat intelligence system using a Convolutional Neural Network and employed sentiment analysis techniques to detect global threats. In this study, LSTM is used to overcome the problems faced by traditional RNNs in capturing long-term dependencies within sequential data. Traditional RNNS suffer from a vanishing gradient problem, in which gradients will diminish exponentially over time, making it difficult for the network to learn long-range dependencies [20]. LSTM tackles this problem by introducing a memory cell with a more complex structure than the simple recurrent unit used in traditional RNNs [18]. LSTM is driven by the sigmoid neural network layers that regulates the passage of information in and out of the cell [21]. Figure 2 illustrates the ADAM-optimized LSTM Model that combines the ADAM optimization algorithm and LSTM networks for predicting political security threats.

Negative emotions such as anger, fear, disgust, fear, and anxiety have been identified as potential indicators of security threats, especially when these emotions are widely expressed in public or digital spaces [8]. For example, anger is often associated with social discontent and can trigger collective actions such as protests or riots, especially in politically unstable contexts. According to studies, anger can be a trigger for aggressive behaviour when an individual or group feels marginalized or oppressed. This shift from emotion to action has been observed in many cases of social instability, where negative sentiment on social media is closely linked to violence or instability in the real world [7, 22].

Fear and related emotions such as extreme fear and anxiety also play an important role in predicting threats. While fear is not an immediate threat, it can cause destabilizing reactions, such as panic buying, mass evacuation, or rioting, especially when influenced by the spread of false information or rumours [23]. Studies in behavioural psychology and security frameworks emphasize that fear increases the perception of vulnerability, making it a useful tool for predicting crises and emergency response strategies [24]. Disgust, often fuelled by moral or ethical outrage, can also increase social division and instability, further contributing to security risks. Sentiment analysis tools, when used to monitor these emotions, have become increasingly accepted for predicting and mitigating threats before they escalate [5].

Razali et al. [8] proposed that emotion is a key variable in determining an opinion or sentiment. Emotions such as anger, fear, disgust, fear, and anxiety can serve as emotional indicators in determining the existence of political security threats in text data. These emotions, as studies have determined, are closely related to the political security domain and have the potential to trigger political events such as riots, coups, terrorism, international wars, civil wars, and political elections, which can lead to negative sentiments or opinions. These opinions or sentiments can be analysed to predict threats in the political security domain [8, 25].

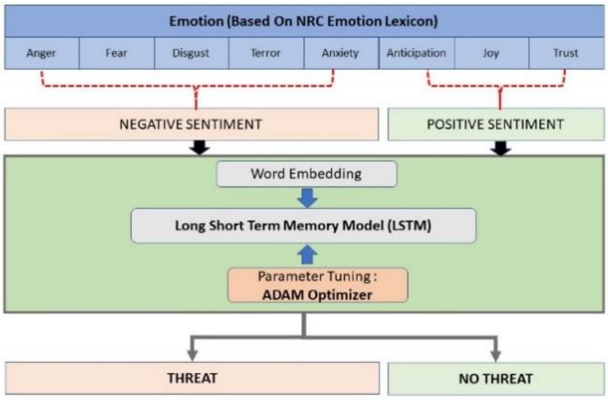

Fig. 2. Political security threat prediction model.

3.5. Parameter tuning using ADAM optimizer

Parameter tuning using the Adam (Adaptive Moment Estimation) optimizer involves adjusting its hyperparameters to improve the performance of a neural network model during training [26]. Adam is a popular optimization method among deep learning model trainers due to its adaptation of gradient descent [27]. Kingma and Ba [28] introduced Adam, based on adaptive estimates of lower-order moments. Empirical results demonstrate that Adam performs well in practice and compares favourably to other stochastic optimization methods.

Traditional first-stage optimization methods such as descending gradient (GD), SGD, SGD with momentum (SGDM), and Adam have been widely used to train convolutional neural networks (CNNs). Among these methods, Adam has demonstrated better solution-seeking capabilities by leveraging momentum and bias correction techniques [29]. Accordingly, many recent studies have focused on improving Adam's performance or combining it with other optimization methods. Notable examples include Adagrad, Yogi, Fromage, diffGrad, and TAdam which have been proposed to further improve optimization performance [16, 29, 30]. Based on previous studies and results that outperformed other optimizers, Adam was chose for the experimental design and simulation purpose.

4. Results and Discussion

The technique we developed was tested using the Python 3.11.1 environment and underwent evaluation on a PC equipped with an Intel® Core™ i7-8650U CPU @ 1.90GHz, 2.11 GHz, 8GB of RAM, a 64-bit OS, and an x64-based processor. We assessed the performance of the ADAM-LSTM approach using a small, labelled dataset of 250 sentences from Malaysian online news sources. To gauge the efficacy of our models, we compared them to the model developed by the researchers cited in reference [8]. We selected their model for comparison because it addresses the same task as our study, which is identifying threats in the political domain, and because it also utilizes the same dataset for evaluation, which is data that is derived from Malaysian online news.

The final phase of this research design is to validate the analysed data. In this phase, this study demonstrated a comparative performance evaluation to validate the proposed theoretical framework. The evaluation test compares the results of precision, recall, accuracy, and F-measure [30].The performance measure involves calculating the accuracy, precision and recall value of the test dataset, and this measure is then used in two phases. The two phases are as follows: Firstly, the evaluations are compared with one another to discern the best optimizer employed in the proposed framework, and secondly, to be fully validated, the selected optimizer is compared to the results of isolated deep learning approaches. Evaluation process commenced after the labelling of data into either positive or negative classes, and the imbalance between the class proportions was addressed. A random subset of sentences was selected to train and test the dataset that used the LSTM deep learning technique, followed by the employment of a confusion matrix, which computed the accuracy, precision, and recall of the DL classifiers, allowing for the comparison of algorithmic performance based on training data labels. Accuracy, defined as the proportion of correctly predicted opinions out of all input opinions to the classifier, is determined by True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. The formula is as shown in Eq. (1).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision is shown in Eq. (2) and is the percentage of true cases of an opinion (of an instance) among all the classified cases of the opinions (of all instances). To determine the accuracy, true positive rate (TP) was used, as shown in the formula below.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Recall is defined as the proportion of properly categorised occurrences of a polarity over the total number of correct instances of the polarity. The formula to calculate the recall values using TP and FN is shown in Eq. (3):

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

The F-score is calculated by dividing the number of true positives by the sum of true positives and false positives, as shown in Eq. (4).

$$F - score = \frac{2TP}{2TP+FP+FN} \tag{4}$$

4.1. Comparative output and benchmarking

The performance of the current model, ADAM-LSTM, proposed model in political security domain, was benchmarked against the baseline hybrid model (Lexicon + Decision tree) by Razali et al. [8] as well as an untrained LSTM model. In this case, untrained model refers to an LSTM (Long Short-Term Memory) network that has not undergone proper training. An LSTM without an optimizer would not have a way to update its weight, leading to poor learning and the model will remain in its initial, random state [31]. In Table 2 and Fig. 3, the ADAM-LSTM model is compared to other currently existing approaches across key metrics: accuracy, precision, recall and F-score [32]. The findings indicate that the ADAM-LSTM model surpasses the hybrid methods in performance, and that the single LSTM model yields the least favourable results.

Table 2. Comparative output of the ADAM-LSTM Model with other methods.

Methods	Accuracy	Precision	Recall	F-Score
ADAM-LSTM	94.0%	94.0%	100.0%	96.9%
Untrained LSTM	40.0%	94.7%	38.3%	54.5%
Baseline Model (Lexicon + Decision Tree)	76.0%	92.7%	80.9%	86.4%

Comparing the untrained LSTM to the baseline model reveals distinct performance differences. The untrained LSTM demonstrates notably inferior performance across all metrics in comparison to the trained LSTM, as it lacks any learned knowledge about the data. Meanwhile the baseline model, which employs a Hybrid Approach, exhibits superior performance to the untrained LSTM, although its results still fall short of those achieved by the trained LSTM. The baseline model has an accuracy of 76 percent, a precision of 92.7 percent, a recall of 80.9 percent, and an F-score of about 86.4 percent, which, while decent, is not the most optimal performance. Lastly, ADAM-LSTM outperforms both untrained LSTM and the baseline model in accuracy, precision, recall and F-score measurements. This highlights ADAM-LSTM's superior ability to classify data more effectively, ensuring fewer classification errors and better overall predictive performance compared to other models in political security domain and the main contribution of this study was evaluated.

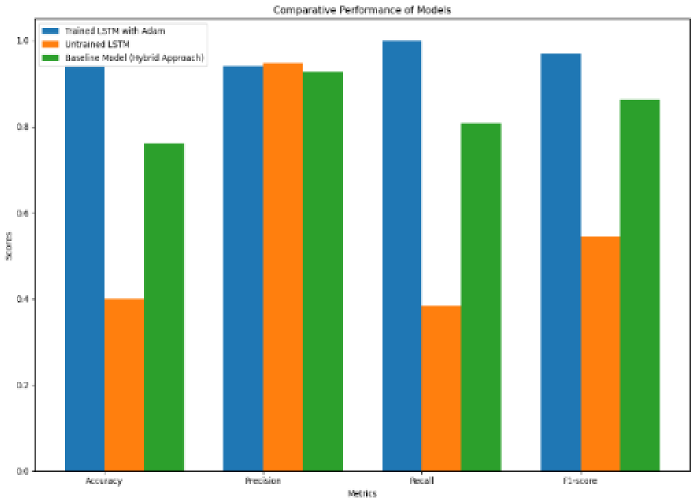

Fig. 3. Comparative performance of ADAM-LSTM model with other methods.

4.2. Area under precision recall (AUC-PR)

In Fig. 4, an AUC-PR of 0.94 indicates that there is high precision being recalled at different thresholds, suggesting that the model performs well in separating positive classes from negative classes.

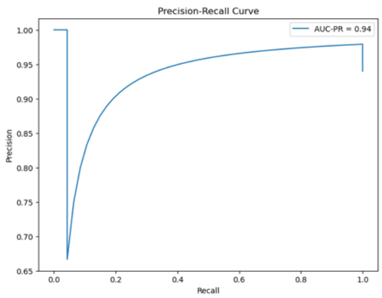

Fig. 4. Precision-recall curve of ADAM-LSTM model.

4.3. Training and validation loss curve

The curves in Fig. 5 show the training and validation loss of the model. Validation Loss and Accuracy are calculated on a separate validation dataset and serve as indicators of how well the model generalizes unseen data [21]. The graph shown shows the train loss (red line) and validation loss (green line) over 100 epochs, which illustrates the model learning process.

The red line, which represents losses during training, decreases consistently, signifying that the model is getting better at understanding the patterns and characteristics present in the training data. This continued decline also indicates that the model is successfully reducing prediction errors on the training data, which is a sign that the model is learning well and becoming more efficient at performing predictions.

In addition, validation loss (green line) also shows a steady decline throughout the exercise. This decrease which is almost parallel to the train loss shows that the model not only learns well on the training data but also has good generalization capabilities on the validation data, which has never been seen during training. The fact that these two losses are almost parallel indicates that the model does not suffer from overfitting, where it manages to avoid overlearning on training data alone, instead works well on the new data being tested.

Both lines show a good downward trend, and there is no significant difference between training loss and confirmation loss. This suggests that the model learns well without relying too much on training data alone. These results show that the model can be effectively used to make accurate predictions on new data. The model shows good generalizations, where it not only gives good results on the training data, but also on the validation data, which is important to ensure that the model does not fit too well with the training data alone.

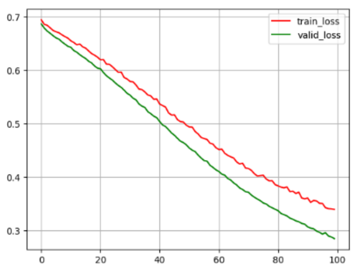

Fig. 5. ADAM-LSTM model loss curves.

5. Conclusions

This research study shows that combining the Adam optimizer with LSTM significantly enhances deep learning models' abilities to predict political threats. This model is not only capable of reshaping the political security threat prediction landscape but can also support researchers' future studies within the national security field. The synergy between the Adam optimizer and LSTM networks offers enhanced accuracy and robustness in national security scenarios by adaptively adjusting learning rates, while also capturing long dependencies that are essential in detecting evolving threats. To summarize, the ADAM-LSTM model introduces new and effective ways to enhance the accuracy, efficiency, and versatility of political threat prediction, making it a significant advancement in the domain of national security.

Abbreviations

ADAGRAD	Adaptive Gradient
ADAM	Adaptive Moment Estimation
CNN	Convolutional Neural Network
GD	Gradient Descent
LSTM	Long Short-Term Memory
RMSPROP	Root Mean Square Propagation
RNN	Recurrent Neural Network
SGD	Stochastic Gradient Descent
SGDM	Stochastic Gradient Descent with Momentum

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