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GeoLocNN: An Efficient NN Approach for Accurate Tweet Geolocation Prediction

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Abstract: Twitter has emerged as the most popular social networking website where users can post their thoughts, opinions, life updates and many more things within a limited number of words which is up to 280 characters. If a user is performing some criminal activities like cyberbullying on such platforms, finding geolocations becomes important. In this article, we predict the geolocation of tweets posted in real time by using neural network techniques. The approach involves extracting features from the tweets and features associated with the tweets. The study introduces a novel deep-learning approach, GeoLocNN, for prediction of geo-location of tweet with higher accuracy. Using a blend of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, the approach outperforms traditional methods in precision and applicability. This provides significant implications for enhancing cybercrime analysis, leveraging spatial dynamics of social media data.

Keywords: *Twitter data collection, geo-tag, geo-location, Twitter location prediction, machine learning, deep learning.*

1. Introduction

Social media has become an important part of our daily lives, providing a platform for communication, opinion expression and information sharing. Of all the social networking sites, Twitter especially stands out as a worldwide platform where users can post a wide range of data which is often related to expressing thoughts, experiences, and opinions that belong to a particular geolocation.. Prediction of the geolocation of tweets has emerged as a potential research area, with implications for understanding the spatial dynamics of social media[1].

Prediction of accurate geolocation is not only a fascinating technical problem, but it has become a necessity now. It offers a way to reveal the geographic background of online discussions, allowing for a more profound understanding of the spatial distribution of sentiment, information, and social phenomena. Keeping the focus on the innovative applications of neural network techniques, this article investigates the complex problem of geolocation prediction for tweets, showcasing the potential of deep learning to uncover hidden patterns and relationships within this unique data domain.

Twitter allows its users the ability to share their location while posting content with the help of GPS, but only 1% of the tweets are geo-tagged as the user wants to conceal their location because of privacy and security issues[2]. Finding the geolocation of the tweet can prove to be very helpful in assisting in identifying cybercrimes such as cyberstalking, cyberbullying and more.

With the advancement of technology and its implications in a wide spectrum, the prediction of accurate geolocation has a diverse domain. This can be used by government agencies to enhance emergency response, disaster management and situational awareness. It not only helps the government but it has its application in private businesses where an accurate geolocation prediction can help them to get their target consumers by offering region-specific products. At its core, the ability to predict the geolocation of tweets using neural networks leads to a new era of context-aware data analytics[3][4].

In this research paper, we have used neural network techniques for the prediction of geolocations of the tweets. We examine the nuances of data preprocessing, feature engineering, model architecture, and training methodologies to reveal the power of deep learning in this context. The tweet location prediction requires the genuine location that can only be extracted using the meta-data of that tweet. There are two types in which the location can be defined: numerical coordinates and class labels in textual format, where the former serves as a more appropriate way to solve country and global problems. Twitter geolocation is stored in coordinates format which is known as the World Geodetic System 1984 (WGS84) and the same datum is used to represent the correct location of the tweet. WGS84 is a reference system that is used to represent the surface of the Earth. It is an unbroken, global reference system that provides a standard for measuring locations on the Earth's surface. To display data on a flat surface, two-dimensional maps, such as the Mercator projection, are commonly used.

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However, these maps have limitations when it comes to displaying numerical values of coordinates. The numerical values of coordinates on a twodimensional map stay in narrow ranges, that can cause incorrectness in location data. The strict ranges of coordinates on a two-dimensional map are due to the alteration caused by the projection used to create the map. This distortion causes the numerical values of coordinates to stay within certain ranges, even though the actual locations they represent may be different. When we predict the geolocation of tweets using longitude, latitude, it becomes important to consider the limitations of two-dimensional maps. The predicted locations may be accurate within the strict ranges of coordinates on the map, but may not accurately represent the actual locations on the Earth's surface. Therefore, it is important to use additional methods, such as Gaussian Mixture Models, to improve the accuracy of geolocation predictions.

$$L = (g_{lo}, g_{la}); g_{lo} \in [-180, 180]; g_{la} \in [-90, 90] \quad (1)$$

To solve this problem, we propose and algorithm TGLoc (Tweet Geo-Location) which use the deep learning techniques, CNN (Convolution Neural Network) and LSTM (Long Short Term Memory).

Some of the approaches discovered are shown in Fig. 1., each of these approaches has some advantages and disadvantages associated with them. The first approach is the content matching system which relies on the content of the tweet. In this we have keyword matching where the keywords are extracted and identified related to specific city and landmarks. Named-entity relationship can identify the named entities like the location specified in the tweet text. Lexical analysis and sentiment analysis can be used to analyse the emotional tome of the tweet which might be a result of some local or cultural event. This approach is very simple to implement and require minima technical expertise, accuracy may be limited and may provide ambiguous results. TF-IDF method is also used to predict the location, where it calculates the importance of word in a class by considering its frequency in other class. This helps us to determine the significance of different words.

$$tf(t_i, c_k) = \frac{f_{ck}(t_i)}{\sum_{j,k} f_{ck}(t_j)} \quad (2)$$

$$idf(ti, c) = \log\left(\frac{|c|}{|\{c_{tj} \in c : t_i \in c_t\}|}\right) \quad (3)$$

where tf (ti, ck) is the frequency of the word ti in class ck, that can be obtaining the term frequency in that class by dividing it by the total number of words in that particular class. Idf(ti) is the inverse frequency that can be calculated by the log of the lotal number of class divided by the number of class in that term. provide an insight to user's network. But this approach highly relies on the information given by the user and the foloowers are usually not the correct measure to predict the location of the user.

The network based approach takes into consideration the user's network and interactions. Analysing user's connections by checking the locations of their connection can provide potential clues through network clustering and path finding algorithms. Identifying the communities within the network and consuming their geographical distribution can suggest the location of the user's tweet. This approach needs large amount of network data in order to make predictions.

The machine learning includes training the large dataset of labelled tweets with geotags included. Machine learning model like supervised machine learning (SVM, Random

Forest etc.,) can learn the relations and predict the location of new tweet. Then the deep learning models like CNN and RNN can very effective in capturing complex relationships between text and their context.

For considering the machine learning algorithms,w e have the first algorithm which is logistic regression (LR), that is a simple linear regression with binary mapping. The function for LR can be given as:

$$f(x) = \frac{1}{1+e(-y)`} \quad (4)$$

where x is the regression function x = my + b.

The second algorithm to be considered is CNN and this has achieved a higher accuracy for our experiment. The function for CNN can be given by:

$$O[i, j, k] = \Sigma(\text{Filter}[m, n, p] * I[i + m, j + n, k + p]) + \text{Bias} \quad (5)$$

Where, i, j, and k represent the output feature map, m, n, and p represent the filter. Filter[m, n, p] represents the weight, bias is a bias term added to the output for each filter.

2. Literature Survey

Prediction of geolocation is a complex task and researchers have developed several techniques overtime to predict the geo location of both the tweets and the twitter users. Prediction technique can also be used if we have to analyse that whether a cybercriminal is situated locally or from a distant location. Geolocation information can be combined with other analysis techniques can give insight into contextual understanding of the cybercrime content such as cyberbullying. Some of the approaches introduced by the researchers for the prediction are:

a) *Using NN for prediction:* Training a neural network to predict the geolocation of a tweet or short text is a notable approach. This approach was introduced by [17] where a neural network is trained on a dataset by learning patterns and the features with different locations. The model was able to predict the location of the tweet based on the text.

b) *The levels of predictions:* The prediction of geolocation happens at different levels: Event level- estimating the location of the event mentioned in the tweet. User level- predicting the location of the tweet who posted it and Tweet level- which determines the location of the tweet.

c) *Fine-Grained prediction:* In recent research, DNN models have been used to predict the geolocation of non-geo-tagged tweets at various levels. These models can calculate locations to neighborhoods, and even longitude and latitude coordinates[10].

d) *Combining Techniques:* Some studies combine techniques like CNNs and bidirectional LSTM to extract features from tweets and associated metadata for accurate geolocation prediction[9]. Some of the work on prediction of geolocation of a tweet is discussed below:

S.no	Author/Year	Work Done & How it is done.	Outcome	Limitation	Future Scope
1	. K. Lutsai et al., 2023 [1]	The article focuses on predicting the geolocation of tweets using a BERTbased model trained on customized data.	The study evaluated the proposed model using geospatial and probabilistic performance metrics.	Only one method is used for evaluation.	Alternative projection methods can be explored such as Robinson projection,
2	. F. Lovera et al., 2023 [4]	The paper presents a framework using NLP, Knowledge Graphs, and Semantic Web to predict the geolocation of tweets.	Results compared with two baselines in terms of F1 score, precision, and recall. - F1 score up to 0.851 within a 10-kilometre radius.	Machine learning models struggle to generalize to unseen places.	Experiments with tweets in other languages can be explored.
3	. K. Lutsai et al., 2023 [6]	The research proposes a methodology using neural networks and BERT-based models to predict the geolocation of tweets with a median error of fewer than 30 km.	The results show a median error of 30 Km on the worldwide dataset and an error of 15 Km on the US dataset.	A median error exists.	Considering alternative projections for geolocation data

4	. M. Abboud et al., 2022 [7]	The paper proposes a multiview learning approach called FLAIR to predict the geolocation of nongeotagged tweets with higher accuracy.	FLAIR model outperforms existing solutions in location prediction.	Tweets considered are not fine and very scattered.	The proposed model outperforms existing solutions, but - Geolocating tweets at finer granularities can be considered.
5	. T. Nithisha et al., 2022 [8]	This study employs naive Bayes, support vector machines, and decision trees as machine learning approaches to predict the user's location from the text of tweets to understand how these text inputs play a role in the problems.		The content of the tweet is brief, and noisy which makes it difficult to extract the location of the tweet.	
6	. R. Mahajan et al., 2021 [9]	In this article, a combination of CNN and LSTM was used to predict the geolocation of real-time tweets.	The approach achieved an accuracy of 92.6% at city-level prediction	Median error of 22.4 Km	Open street mapping from Google can be considered. The dynamic movement of the user and images posted by users on the Twitter timeline can also be looked at as a future work.

7	. F. Dutt et al., 2021 [10]	The article proposes a set of deep neural network techniques using natural language processing to predict the geolocation of non-geo-tagged Tweet posts using neighbourhood, zip code, and longitude with latitudes.	Geolocation prediction shows good results and empowers end-users to correlate the location.	Model is not fit for untrained data.	Can be taken further to correlate more variables to get refined results.
8	. P. Mishra et al., 2020 [11]	In this paper, a neural regression model was used to identify the linguistic intricacies of a tweet to predict the location of the user and the final model identified the language embedded in the tweet and predicted the location.	BiLSTM regression model – Linguistic analysis of tweets	The model is not used on a benchmark dataset.	Explore the use of additional linguistic markers. Investigate the model's performance on different datasets

9	. Y. Almadany et al., 2020 [12]	A new efficient and accurate algorithm is proposed to predict the country location of a Twitter user using his or her public information only and significantly outperforms other location detection algorithms by using Twitter users from different countries.	The proposed algorithm outperforms other location detection algorithms. - Results showed significant improvement in predicting user location.		Future work includes refining the algorithm.

Proposed Prediction Algorithm

In the article, we have proposed an algorithm to check the geo-location of the tweets. The input to this algorithm is the dataset which is obtained using the Twitter API. The API provides the feature to get the geo-tags of the tweets, if available. To extract the location-specific feature from the tweets we have used CNN and LSTM techniques as combining these two helps in extracting the local as well as the global features of the tweets. CNN, Convolution Neural Network is a type of neural network that is used in various computer vision and image processing tasks and has shown great performance in various other fields. It is processed in multiple feature extraction stages that automatically learn representation from data which makes it powerful in many tasks such as image processing, computer vision, segmentation etc. As CNN has evolved, the new architecture has been employed in multi-path information processing, width, feature-map exploitation, channel boosting, and attention. The recent development of CNN has improved the capacity of deep CNN which is now even used for video processing, natural language processing and task of speech recognition[13][14].

LSTM, Long Short-Term Memory is used for sequence modelling problems. LSTM is commonly used for preprocessing and post-processing which helps in creating a complete algorithm [15]. LSTM is a type of deep learning technique used for trend forecasting in the currency market [16].

The features used to perform the prediction task are screen name, user profile location and the content posted. The dataset is divided into ratios of 80 and 20, where 80 is used for the training and testing is being done on the rest of 20. After installing the required dependencies, the collected tweets are transformed into numerical vectors from text data using BERT (Bidirectional Encoder Representations from Transformers) or a similar natural language processing model. These vectors are capable of capturing the semantic meaning of the text. The input to the experiment is the word vector which we have extracted using BERT. If the dataset collected does not already include the geolocation information then use the geocoding service to obtain the desired labels. Reverse geocoding can be used for converting latitude and longitude coordinates into location details such, as city and state. The newly constructed vectors are embedded in the matrix Vv. We have also used a patch filter of size 3 and 5. Patch filters are used to extract the features in CNN where a lower number extracts the local features and a higher number extracts the global features, here 3 is used for the local feature extraction and 5 is used for the global feature extraction. Also, each filter will capture different text patterns. When the matrix is embedded then generating Eigen Values through Convolution is important.: This step is needed in the context of word embeddings but may involve using convolutional neural networks (CNNs) to analyze the word embedding matrices[18].

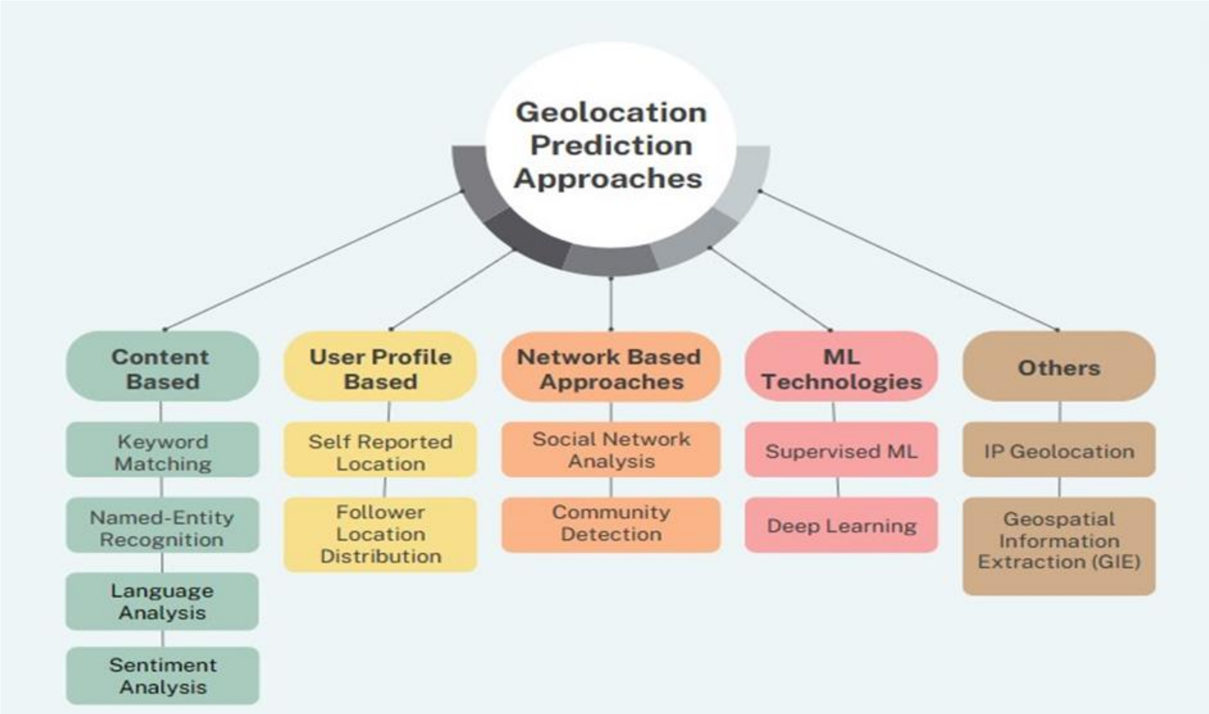

Figure 1: Figure denotes the several approaches which can be used for the prediction of geo-location of a tweet.

The model can be explained as:

1. **Data Preprocessing and Acquisition**: This step involves installing the necessary Python libraries such as Numpy, Pandas, and Seaborn. These libraries are essential for data manipulation, analysis, and visualization tasks. The training, development, and test data are read from CSV files into pandas DataFrames. This step involves loading the data into memory for further processing and analysis. The training data is preprocessed, which may involve tasks such as handling disappeared values, normalizing the data, or dropping irrelevant rows. This step ensures that the data is in a suitable format for training the neural network.
2. **Feature Engineering and Network Architecture** Design:This step involves preparing the input and output data for the neural network. It includes tasks such as upsampling the training data if necessary, converting the feature arrays and target variables into numpy arrays, and preparing the development set input and output data similarly. Here, the architecture of the neural network is defined. This includes creating a Sequential model and adding Dense layers with specified activation functions. The number of units in each Dense layer is determined by the layer_units list.
3. **3. Build Sequential Model with Dense Layers:**The Sequential model is created, which serves as the foundation for building the neural network architecture. The Sequential model allows you to create models layer-by-layer in a step-by-step fashion. Dense layers with specified activation functions are added to the Sequential model based on the layer_units list. The first layer specifies the input dimension, while subsequent layers are added normally. This step involves defining the structure of the neural network by adding layers that perform mathematical operations on the input data. We have also added attention mechanism where an attention layer is added to assign weights to different parts of the LSTM output based on their relevance in the task of geolocation prediction. Also, we have used ReLU for further featire extraction.
4. **4. Compile Model:** The model is compiled using the Adam optimizer and a specified loss function. This step also involves specifying the metrics to be evaluated during training, such as accuracy. Compiling the model prepares it for training by specifying the optimizer, loss function, and metrics to monitor.

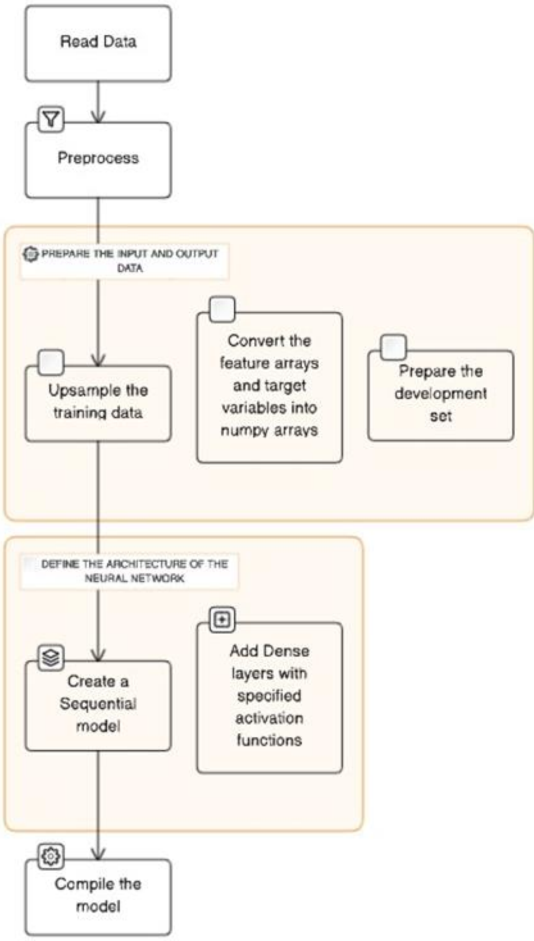

Figure 2 Block Diagram the proposed model for geolocation prediction

5. Train and evaluate model for training data (DTrain): The model is trained using the training data. This step involves fitting the model to the training data, specifying the batch size, number of epochs, and validation data for model evaluation. During training, the model learns to make predictions by adjusting its internal parameters based on the training data. The trained model is evaluated to assess its performance. This step involves evaluating the model's performance on the training data and validation data. Evaluation metrics such as accuracy, loss, and other relevant metrics are computed to gauge the model's performance.

6. Train and evaluate model for test data (DTest): The model is trained again using the test data. This step is similar to training the model with the training data, but it uses the test data for evaluation. Training the model with the test data allows for an additional assessment of its performance on unseen data. The trained model is evaluated again, this time using the test data to assess its performance on unseen data. This step provides a final evaluation of the model's performance on the test data, which is crucial for understanding how well the model generalizes to new, unseen examples.

This detailed breakdown provides a comprehensive understanding of the workflow involved in building, training, and evaluating a neural network model. Each step in the workflow contributes to the overall process of developing and assessing the model's performance, from data preparation to model training and evaluation.

Algorithm 1: ***ITGT prediction Algorithm***

Input : CSV file as a dataset

Output : A trained deep learning model for predicting tweet geolocations.

1 Install dependencies like Numpy, pandas, and. Seaborn.

2 Connect with Twitter using the consumer API key and access token.

3 Fetch the word vector V= {v1,v2,…..,vn} using any pretrained model such as BERT and its corresponding Tokenizer

4 Prepare the data by spiliting the Tweets into DTrain and Dtest .

5 Initialize the model with appropriate hyperparameters and prepare it for training.

6 Define a function create_attention_model to build the neural network architecture: inputs = tf.keras.Input(shape=(X_train.shape[1], embedding_dim)) # Input layer

7 For each unit d in input

8 lstm_1 = tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(units, return_sequences=True))

9 lstm_2 = tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(units))(lstm_1)

10 attention_weights = tf.keras.layers.Attention()([lstm_2, lstm_2]) # Calculate attention weights

11 context_vector = tf.keras.layers.dot([attention_weights, lstm_2], axes=1) # Weighted sum

12 if units == input[0]: # For the first layer, specify the input dimension

13 model.add(Dense(units, activation='relu', input_dim=300)) 14 else:

15 model.add(Dense(units, activation='relu'))

16 Compile the model using Adam Optimizer

17 Train the model for DTrain

a. Fit the model to the training data.

b. Specify the batch size, number of epochs, and validation data.

18 Evaluate the model

19 Repeat the steps for Dtest

We also propose to further refine this algorithm to analyze the missclassifed tweets and learn from their pattern and characteristics. Doing this can further increase the accuracy of the algorithm. Here are some ways to further enhance the algorithm:

1. Implement data augmentation techniques to increase the diversity of training data.
2. Fine-tune the hyperparameters of the model for better performance.
3. Explore different neural network architectures to improve the model's accuracy.
4. Conduct cross-validation to assess the model's generalization ability.
5. Incorporate attention mechanisms to focus on important parts of the input sequence.
6. Regularize the model to prevent overfitting and improve robustness.
7. Optimize the training process by adjusting learning rates and using early stopping techniques.
8. Evaluate the model's performance using different evaluation metrics to gain deeper insights.
9. Enhance the preprocessing steps to handle noisy or incomplete data effectively.

These enhancements can help improve the algorithm's performance and effectiveness in analyzing Twitter data to determine the probability of a Tweet originating from a city.

3. Results and Discussion

Many experiments have been conducted in this field before predicting the geo-location of the tweets which comprises different machine-learning approaches such as Logistic Regression, KNN and random forest. With the application of these algorithms, we have applied CNN sequential model to our experiment. Because we see that the dataset has a big class imbalance, there was a continuous need for upsampling and downsampling the data. Upsampling is used when a dataset has a class imbalance, meaning one class of the target variable is understated, upsampling involves randomly duplicating samples from the minority class to balance the class distribution, in contrast, downsampling when a dataset has a class imbalance, downsampling involves randomly removing examples from the majority class to balance the class distribution. This is done to prevent the model from being biased towards the majority class and to improve its ability to make accurate predictions for the minority class. We have used different models for classification model evaluation which are precision, recall, accuracy, F1-score, and confusion matrix. Precision is called positive prediction value, which measures the true instance out of the total instance. Recall measures the fraction of relevant instances that were retrieved. It focuses on the ability of the model to find all the relevant cases within the dataset. Accuracy is the percentage of true prediction on testing data. F1-score calculates the harmonic mean of the macro-averaged precision. The confusion matrix is used to compute the performance of the model. The experiment was conducted using Python and Jupyter notebook.

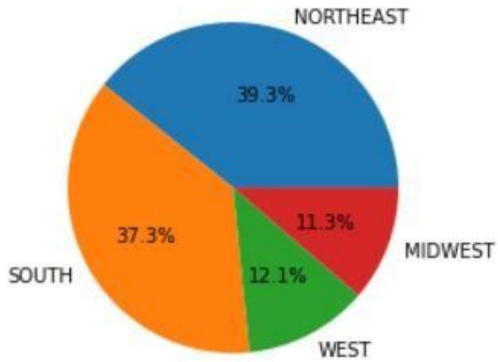

Figure 3. The Distribution of Target Labels

The above graphs depict the class distribution of the dataset, and the chart after dropping the duplicate rows. After the deletion of duplicate rows, there is a shuffling of data within the dataset to make sure that similar data is not grouped.

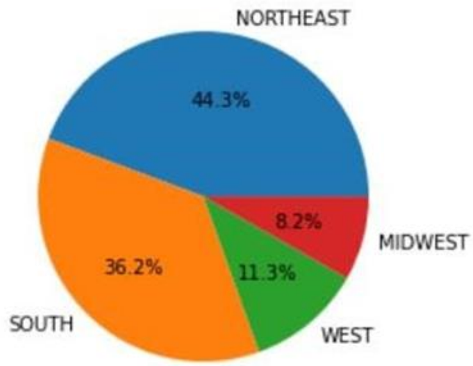

Figure 4: Tweet Duplicacy

	precision	recall	f1-score	support
East	0.00	0.00	0.00	16228
Eastb	0.00	0.00	0.00	15084
Northa	0.39	1.00	0.56	51336
South	0.00	0.00	0.00	48883
accuracy			0.39	131531
macro avg	0.10	0.25	0.14	131531
weighted avg	0.15	0.39	0.22	131531

Figure 5: Training Performance

Now, after all these steps for the training, the models are applied to check the accuracy of the test set.

1. Logistic Regression:

LR technique if applied after the training set and it can be observed that it does not give promising results as this technique is not able to handle the data when the variables are independent. The results from the LR technique is given below:

***** Performance ******

	precision	recall	f1-score	support
East	0.32	0.00	0.01	16228
Eastb	0.23	0.00	0.00	15084
Northa	0.48	0.61	0.53	51336
South	0.43	0.57	0.49	48883
accuracy			0.45	131531
macro avg	0.36	0.30	0.26	131531
weighted avg	0.41	0.45	0.39	131531

Figure 6: LR Results

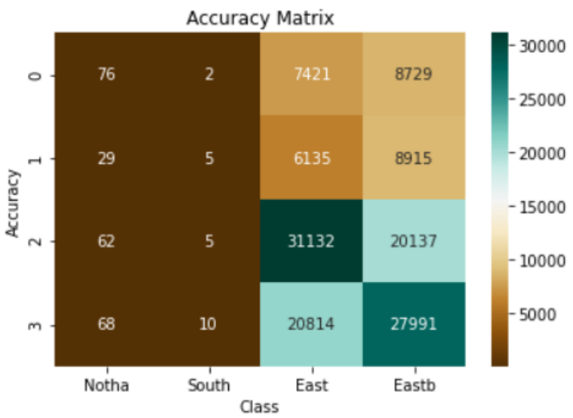

Figure 7: Heatmap for accuracy

2. KNN:

This technique is applied to check the accuracy and the classifier accuracy was less than LR model as shown below:

	precision	recall	f1-score	support
MIDWEST	0.17	0.29	0.22	151
NORTHEAST	0.58	0.32	0.41	572
SOUTH	0.19	0.29	0.23	173
WEST	0.09	0.14	0.11	104
accuracy			0.29	1000
macro avg	0.26	0.26	0.24	1000
weighted avg	0.40	0.29	0.32	1000

Figure 8: Accuracy of KNN

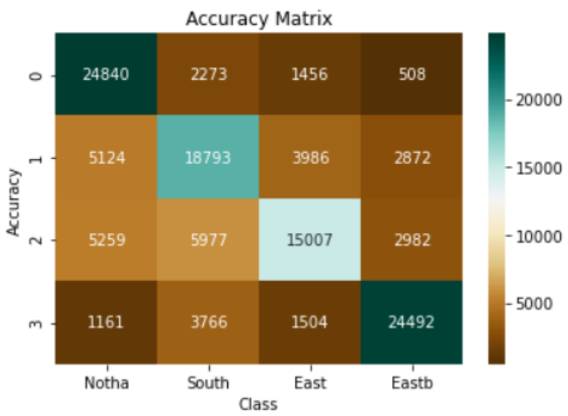

Figure 9: Heatmap for KNN

3. Random Forest:

The results of RF are given below, as it gives an accuracy of 39%.

	precision	recall	f1-score	support
MIDWEST	0.15	0.05	0.08	1484
NORTHEAST	0.44	0.52	0.47	4295
SOUTH	0.41	0.47	0.44	4266
WEST	0.13	0.09	0.11	1430
accuracy			0.39	11475
macro avg	0.28	0.28	0.27	11475
weighted avg	0.35	0.39	0.36	11475

Figure 10: Random Forest Accuracy

4. CNN:

CNN model has been applied to the model where the epoch is 20 and the batch size was set to 500. The results are given below, with an accuracy of 65%.

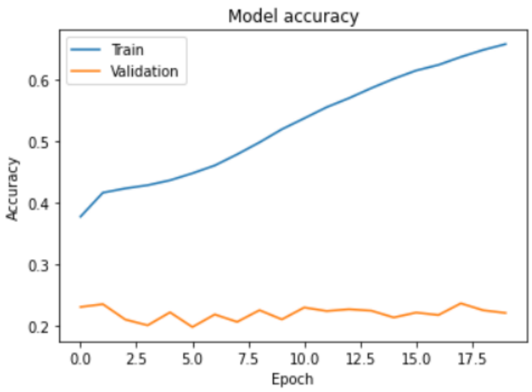

Figure 11: Model Accuracy

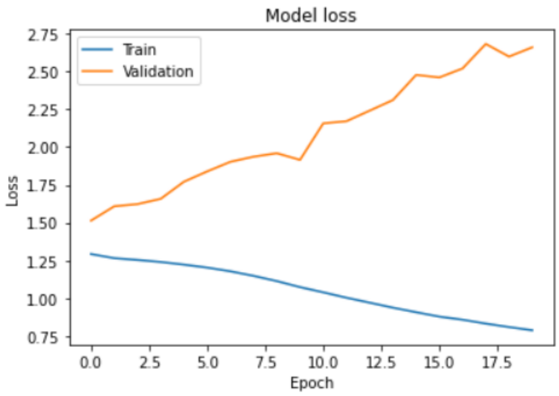

Figure 12: Model Loss

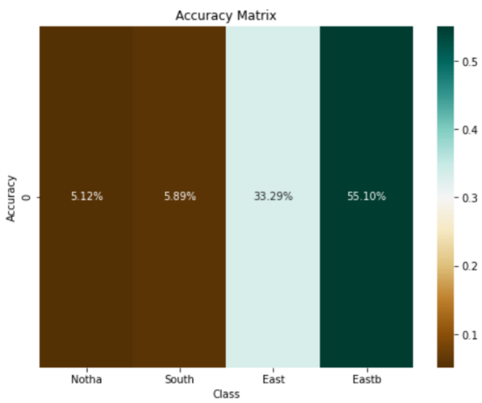

Figure 13: Heatmap.

Table 1 shows the comparison of all the classifiers in terms of accuracy where CNN has the highest accuracy score and can be explored further to enhance the accuracy of the geolocation prediction problem.

Table 1 Accuracy Comparison

Classifier	Accuracy
CNN	0.65
Logistic Regression	0.45
Random Forest	0.39
K nearest classifier	0.29

4. Conclusion

In this research, we investigate the effects of deep learning model along with the attention mechanism to predict the realtime location of tweets. For this, we propose an algorithm that we name ITGT, using a combination of CNN and LSTM. We can consider the task of geo-location prediction as a classification problem where the aim is predicting the city for a single tweet or it can be considered as a multiclass regression problem where the aim is predicting the latitude or longitude of the tweet. We have used BERT for pre-trained wor vectors and used Bidirestional LSTM with attention layer. The attention mechanism allows the model to focus on the relevant parts of the each tweet for geolocation prediction which has proved to be efficient when compared to the model without attention. We have achieved result of CNN as 65% accurate, and have observed significant improvements compared to baseline models without attention mechanisms. This also suggests that attention technique can provide effective insights for models while splitting with textual data like tweets, where location specific information might be dispersed through the text. This algorithm has a limitation of high computation cost and the lack of geo-tagged data due to privacy concerns of the user. We also can incorporate the open street map for future work of this research.

Author contributions

Atika Gupta: Conceptualization, Methodology, Writing **Priya Matta**, **Bhasker Pant:** Reviewing and supervising.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] K. Lutsai & C.H. Lampert (2023). Geolocation Predicting of Tweets Using BERT-Based Models. arXiv preprint arXiv:2303.07865.

[2] S Hale, D Gaffney,M Graham (2012) Where in the world are you? Geolocation and language identification in twitter. Proc ICWSM 12:518–521

[3] T.A Arafat, I. Budi, R. Mahendra and D.A Salehah, Demographic analy- sis of candidates supporter in twitter during indonesian presidential election 2019. In 2020 International Conference on ICT for Smart Society (ICISS) (2020), IEEE, pp. 1–6.

[4] J. Bakerman, K. Pazdernik, A. Wilson, G. Fairchild and R. Bahran Twit- ter geolocation: A hybrid approach. ACM Transactions on Knowledge Discovery from

Data (TKDD) 12, 3 (2018), 1–17.

[5] F. Lovera, Y. Cardinale, D. Buscaldi & T. Charnois (2023). A Knowledge Graph-Based Method for the Geolocation of Tweets. In Workshop Proceedings of the 19th International Conference on Intelligent Environments (IE2023) (pp. 53-62). IOS Press.

[6] K. Lutsai & C. H. Lampert (2023). Geolocation Predicting of Tweets Using BERT-Based Models. arXiv preprint arXiv:2303.07865.

[7] M. Abboud, K. Zeitouni & Y. Taher (2022, November). Fine-grained location prediction of non geo-tagged tweets: a multi-view learning approach. In Proceedings of the 5th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery (pp. 82-91).

[8] T. Nithisha, T.D. Reddy & M. Sangeetha Position(2022) Forecast on Twitter Using Machine Learning

Techniques.

[9] R. Mahajan & V. Mansotra (2021). Predicting geolocation of tweets: using combination of CNN and BiLSTM. Data Science and Engineering, 6, 402-410.

[10] F. Dutt & S. Das (2021). Fine-grained geolocation prediction of tweets with human machine collaboration. arXiv preprint arXiv:2106.13411.

[11] P. Mishra (2020, December). Geolocation of tweets with a BiLSTM regression model. In Proceedings of the 7th Workshop on NLP for Similar Languages, Varieties and Dialects (pp. 283-289).

[12] Y. Almadany, K.M. Saffer, A.K. Jameil & S. Albawi

(2020). A novel algorithm for estimation of Twitter users location using public available information. International Journal on Smart Sensing and Intelligent Systems, 13(1), 1-10.

[13] Asifullah, Khan., Anabia, Sohail., Umme, Zahoora., Aqsa, Saeed, Qureshi. (2020). A survey of the recent architectures of deep convolutional neural networks. Artificial Intelligence Review, doi: 10.1007/S10462-020-09825-6

[14] Hu, Hui., Kang, Wenxiong., Deng, Feiqi. (2017). CNN model, CNN training method and vein identification method based on CNN.

[15] Bushun, Liang., Siye, Wang., Yeqin, Huang., Yiling, Liu., Linpeng, Ma. (2023). F-LSTM: FPGA-Based Heterogeneous Computing Framework for Deploying LSTM-Based Algorithms. Electronics, doi: 10.3390/electronics12051139

[16] Pooja, Bharadwaj. (2023). Encoder–Decoder (LSTMLSTM) Network-Based Prediction Model for Trend Forecasting in Currency Market. doi: 10.1007/978-981-19-6525-8_17

[17] Philippe Thomas and Leonhard Hennig (2017), "Twitter Geolocation Prediction using Neural Networks." In Proceedings of GSCL

[18] Ribeiro, H. V., Lopes, D. D., Pessa, A. A., Martins, A. F., da Cunha, B. R., Gonçalves, S., ... & Perc, M. (2023). Deep learning criminal networks. Chaos, Solitons & Fractals, 172, 113579.