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A Robust Deep Learning Ensemble System for Social Media Rumour Classification

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Abstract

People use social media platforms like Twitter and Facebook to post, comment on, and share millions of messages every day. Online social networks including Instagram, Reddit, Linkedin, etc are globally expanding because of the increasing growth of social networks. Rumour detection is an important role in social networks. The widespread spread of rumours on social media sites has the potential to harm society. The automatic rumour identification is considered difficult since it necessitates some preliminary information in the advanced model for the determination of unrelated or similar information reported onto real information. This phenomenon has drawn a lot of attention to research on rapid rumour detection. In this paper, we proposed a model for rumour detection using Deep learning techniques of Discriminative model of Recurrent neural network (RNN), generative models of Deep Belief Network (DBN) and Hybrid model of Long short-term memory (LSTM) and compare the accuracy using precision recall and F1-score. Results prove that the proposed approach detects rumour efficiently.

Keywords: Recurrent neural network, Deep Belief Network and Long short-term memory, Rumour Detection

I. Introduction

In today social media-driven world, it is vital to detect and prevent rumour propagation from spreading. The term rumour refers to any item of information that has been widely spread in the public domain but has not been proven to be true by solid evidence. It spreads like wildfire, especially during times of crisis, and is widely accepted by the general public and government [1]. If users are looking to keep information on social media sites like Facebook, WhatsApp, Twitter, and Instagram (to name a few) safe, there are several strategies and technologies you may use to do so. These systems conform to necessary regulations or established norms in order to apply rubrics for accurate and acceptable content filtering, and this relies entirely on the advanced models including artificial intelligence, content moderators and user reporting, in order to do so [2]. However, because of the increased data volume that

includes tiredness and content that comes with proper sorting via problematic messages, the moderators are unable to communicate their methodology and code of practise to the users, who, as a result, are unable to understand them. Furthermore, rumours travel fast and aggressively [3], creating a vicious cycle. It is not uncommon for disproved rumours to resurface after they have been debunked in the first place. It is also critical at this moment to automate the debunking of rumours and to prevent their spread through social media [4].

The debunking of a rumour usually consists of four steps: recognising the rumour, investigating it further, and finding its source and truth [5]. It is essential that all of these sub-tasks are combined into a cohesive framework for rumour resolution. If you want to get the most out of the subsequent sub-tasks, it may be beneficial to start with the identification of rumours in order to maximise your results. The majority of microblog rumours are tied to a certain collection of events, and the length of their lifecycle is determined by that collection of events [6]. Long-standing rumours can be indicative of a persistent and long-lasting personality, but a major news event with no prior history might exacerbate the spread of rumours in a short period of time. Many investigations have discovered that there is a large delay between the appearance of an untruth and its resolution [7].

Being able to quickly and accurately verify the veracity of rumours is a key aspect of preventing the spread of false information. Due to the fact that the intensity is at its highest peak at the beginning of an event, debunking is crucial at this point. Automatic rumour identification can be assisted by computationally intelligent models that are self-learning and generalizable, as well as by machine learning techniques. Various researchers [8]-[13] documented the usage of a variety of content-delivery, user-management, and network-management capabilities. With the use of linguistic semiotic characteristics, it is possible to detect rumours at an early stage. Vocabulary, structure, and grammar are the most fundamental textual qualities that may be retrieved from both spoken and written language, respectively. When it comes to breaking news, rumours that can have a substantial impact on it are frequently circulated through trending topics and hashtags. It is therefore vital for a live news or an event to absorb automatically a hidden and a new element of a natural language and its related correlations from text in order to provide accurate coverage. As a result, the learning model and the feature set that an automates rumour generator utilises have an impact on the rumours they generate.

When it comes to categorising social media posts, it is vital to determine whether or not they are accurate or false statements [12]. The Text classification feature is available. Data engineering is a vital sub-task in the process of changing data into a structure that is suitable for machine learning. As a result, text-based rumour detection is challenging since the classifiers are unable to accurately categorise the disinformation, resulting in a reduction in both the detection rate and accuracy of the system. Many issues in natural language processing have been resolved through the use of deep learning models, which have produced results that are state-of-the-art. As an example, prior research has shown that feature selection can speed up machine learning by reducing the amount of irrelevant and redundant features that must be included in the model training. The overfitting and curse of dimensionality is hence avoided as

a result of significant increase in the classifier efficiency and accuracy. The selection of features hence includes wrapper methods, filter methods, and embedding models [8].

Using filter approaches that evaluate the significance of each feature in isolation, selection algorithms are created that rely on the underlying characteristics of the data. A greedy approach to selecting the finest feasible combination of attributes is taken by wrapper techniques, in contrast. Embedded methods, which are approaches to model selection that occur during model fitting, are referred to as such. The most common problem with filter approaches is that they are both fast and model-independent, but they frequently fail to select the optimal subset of features [11]. Model performance on all feature subsets is typically evaluated using wrapper techniques, which help to determine the optimal subspace for a certain algorithm and its associated algorithm. This results in models that require a significant amount of computer power and are, in many situations, unworkable. As a result, embedded approaches are often favoured over other accessible options because they mix the best of both realms. This is because they combine the best of both worlds [12]. It is proposed in this paper to combine deep learning techniques such as discriminative RNN, generative DBN models, and a hybrid long-short-term memory model in order to develop a rumour detection system. The accuracy of the system is evaluated using measures such as precision recall and f1-score. Evidence has been gathered to suggest that the strategy under discussion is effective in terms of detecting rumours.

II. Literature Review

We face substantial risks of incorrect information when it comes to distributing and exchanging knowledge in the new social media ecosystem, which is a big threat to our safety. When discussing online information fabrication, the terms misinformation (honest mistakes), disinformation and misinformation are frequently used interchangeably to mean online information fabrication. This varies depending on the authenticity of the material and the purpose for which the information was created, produced, or distributed, among other factors. However, disinformation refers to completely false statements that have no foundation in reality and are intended to harm a person, group, organization, or country. Using the example of erroneous information, while it is a mistake, it is not intended to cause harm to anyone; rather, it is a misunderstanding. The term mal-information refers to information that is based on the truth but has been misinterpreted or manipulated with the intention of harming others.

Unavoidably, we have been subjected to a never-ending barrage of online deceptions, fabrications, and hate crimes due to the disordered information [14] afflicted over the social networks. This network is seamless and effective alternative for criminals to disseminate gossip or fraudulent stories because of the ease with which accounts can be created, the accessibility of postings, the large range of options, and the viral nature of the medium. Fake news, alternative facts, and hate speech are all aided and abetted by the economics of social media [15-17]. When someone makes an unsubstantiated allegation, it is called a rumour. The rumor-resolution process is divided into four steps, which are illustrated in the below:

Rumour Detection: It is necessary to provide an input stream of postings into the rumour identification step, which uses a binary classifier to determine whether a post should

be regarded as true or false based on its content. When it comes to dealing with rumours that are just getting started, this is a necessary skill set to have. Rumour Tracking: Social media networks are continuously monitored for posts that characterise the rumour once it has been given to it, either in descriptive form or in the form of keyword phrases. Rumor Tracking is a service that allows you to track down rumours. After that, you will get a list of posts that are related to one another. Stance Classification: In the rumour monitoring component, each linked post that is produced is labelled with an attitude such as supporting, denying, or questioning, and the orientation of each post is determined by this aspect of the component.

Veracity Classification: The veracity of a rumour is judged based on the outcomes of the preceding two components, as well as other available web information, among other things. Identification of the source of a rumour or piece of information is an extra subtask to be completed.

Considering the sheer volume and quickness with which user-generated content is being shared on social media, the ability to detect rumours is essential. Social media facilitates the dissemination of information regardless of source verification of the information. The ease with which information may be passed along and broadcast, as well as the reality that there is no means to check the authenticity of the information, serve to fuel speculation. On the other hand, when users are exposed to hazardous or unpleasant content, this can be detrimental. However, the formation of virtual alignments based on shared interests on many social media platforms may result in the construction of echo chambers, in which individual own points of view are magnified and reaffirmed. Unconfirmed posts are more credible in echo chambers since they are not verified. Because the information is coming from their own people, when a member of a group hears it, they may assume it is accurate.

A large number of studies have documented the automatic detection of rumours in social media data, in specific Sina Weibo and Twitter, among other platforms. Zubiaga et al. [18] reported their findings in the journal Science. The outcomes of a comprehensive investigation conducted by Zubiaga et al. [19] were given by the researchers. Rumor resolution was broken down into smaller sub-tasks, each of which the writers researched in depth in the existing literature before putting together a final answer. We have achieved success in detecting rumour posts in microblogs using a number of different machine learning and deep learning algorithms. Kumar and Sangwan [20] employed a variety of machine learning algorithms to detect rumours in their research. Some rumour detection and prediction models have been trained using a variety of features [21-25], which include user-based, text-based, and network-based features. The models associated with deep learning are used recently to assist the textual rumours detection. Outstanding accuracy is obtained using LSTM with RNN and LSTM with hybrid CNN, attention-based RNN, and RNN networks, among other techniques. Jin et al. [26] have also proposed detection model on multimodal rumour that combines attention RNN with LSTM, which they call attention-based LSTM. CRF, or the classifier model in a sequential manner that was created using Zubiaga et al. [27]. It is suggested that a hybrid model combining deep neural network modelling with machine learning optimizations be developed as a result of this research[28]-[30].

III. Proposed Method

To propose a model for the identification of rumours, deep learning approaches such as the discriminative RNN model, generative models of DBN, and a LSTM model are utilised in conjunction with each other Figure 1. When rumours begin to circulate on social media, they can be quickly found by conducting a keyword search for the relevant terms. The substance of these postings provides a more accurate description of the rumor-related happenings detailed in these postings. The rapid spread of rumours is facilitated in part by the forwarding of relevant postings and the comments left on them.

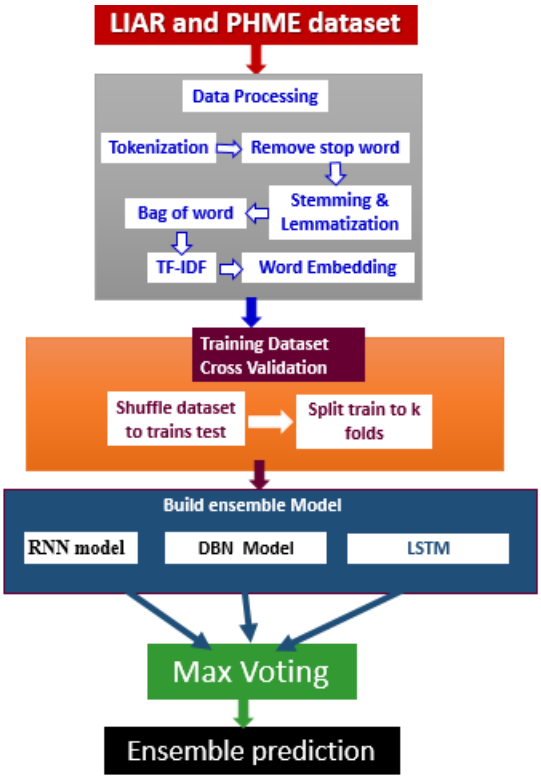

Figure 1: Ensemble Prediction model

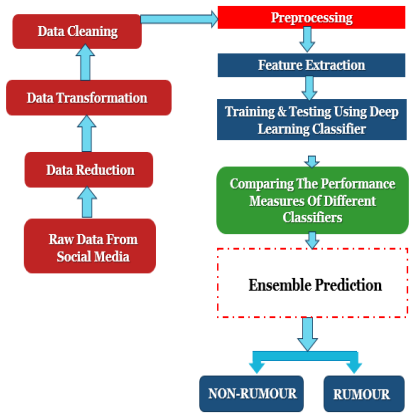

Figure 2 Overview of Proposed Method

The proposed structure for rumour detection Rumors and non-rumors were sorted out of the microblog data set, and the results were analysed. As a result, when the data was randomly mixed, the distribution of the training, verification, and test sets was essentially equal. For each event in the jumbled data set, there are many forwarding and comment data points to consider. The data is then divided into 20 categories based on the length of the time series. Following the grouping of event data, each paragraph of event data is regarded as a single paragraph of text. Additional vectorization of text is accomplished by using the Doc2Vec vectorization approach. Therefore, the sentiment polarity analysis approach is being utilised to determine the text sentiment polarity and the associated sentiment tendency attributes, which are both derived from the text. The final stage is to combine all three sets of sentiment tendency features into a single set of characteristics. The convolutional neural network model used the 20 sets of vector matrices as input, as well as an attention mechanism, throughout the training process

A. RNN :

The RNN, which is a type of artificial neural network that is composed of three different layers that includes: the input layer, the hidden layer, and the output layer. There are two ways in which an RNN differs from a standard network including feedforward neural network (FFNN). An RNN, in contrast to the FFNN, has connections between its nodes that are all in the same hidden layer.

The hidden layer inputs contain the results of current input and the hidden layer before it in the hierarchy. It is possible to provide a more precise description of dynamic behaviour since the RNN unique structure, which draws on previously learned information to predict the pattern of the current step. RNNs with a memory function were then looked into and used for the prediction of time series in the future.

B. Data Preprocessing:

Twitter Dataset: Preprocess the Twitter dataset by cleaning and tokenizing the text data. Handle special characters, mentions, and URLs appropriately. Consider using techniques like stemming or lemmatization.

Liar Dataset: This dataset contains textual statements. Preprocess the text data similarly to the dataset.

C. Feature Representation:

Convert the preprocessed text data into a numerical format that can be fed into the DBN. This often involves techniques like TF-IDF or word embedding's

.

D. DBN Architecture:

Build the DBN architecture. This typically involves a stack of Restricted Boltzmann Machines (RBMs) for unsupervised pre-training, followed by a fine-tuning phase using backpropagation for supervised learning.Use the pre-trained DBN as feature extractors**.**

E. Pre-training:

Pre-train the RBMs layer by layer using the Twitter dataset. This initializes the weights of the DBN. rbm.learning_rate = 0.06 rbm.n_iter = 20 rbm.n_components = 100

RNNs are unable to maintain a good recollection of data when the time interval is too long and the gradient disappears. As a result, multiple improved RNN models have been developed, including the LSTM with a fundamental structure, which is widely used for prediction of instances i.e. rumour data. The memory units are computed using a number of activation

functions, which can be found here. Because of this, its use in the field of hydrology has been limited.

***F.Deep Belief Network**:*

A DBM is a set of RBMs that is trained in order to learn the parameters of the model that includes *e*, a model parameters that is trained using the RBM, which is expressed as: $p(v|h,e)$, and previous hidden vector distribution, $p(h|o)$ and this results in probable generation of visible vector and this is expressed as: $p(v|h,e)$.

$$p(v) = \sum_h p(h|o)\, p(v|h,e)$$

Once *e* has been trained, this model that is replaced with trained with the vectors hidden layer activity $H = h$ and this is considered as the training data of the visible layer from an another RBM while keeping p ($v|h$, e) constant. The variance lower bound on the training data probability of the composite model is improved as a result of this modification. The following are three rules to keep in mind when dealing with people:

- Following a certain threshold, performance starts to level off at a certain level of accuracy.
- The performance increases in direct proportion to the number of layers used.
- The more times each RBM is trained, the better its performance will be.

Unsupervised training in the DBN architecture allows for the extraction of features for dimensionality reduction through the use of the DBN algorithm, which is implemented in the DBN architecture. DBN, on the other hand, is used for classification when the labels of the classes are related to the features of the features. An alternative class target encoder than the standard one-of-K softmax encoder may be advantageous in this design because there are so many possible classes and the frequencies for each of them are not evenly distributed.

F. LSTM:

Using Long Short-Term Memory (LSTM) networks for rumor detection with Twitter and Liar datasets involves several steps. LSTMs are a type of recurrent neural network (RNN) that can effectively capture sequential patterns in data. Here's a high-level overview of the process:

G. Data Preprocessing:

Twitter Dataset: This dataset may contain tweets labeled as either rumors or non-rumors. Preprocess the text data by tokenizing, removing stopwords, and handling special characters and mentions.

H.Liar Dataset: This dataset contains statements labeled as true, mostly true, half true, barely true, false, and pants on fire. Preprocess the textual data by tokenizing and cleaning.

Text Representation: Convert the processed text into a numerical format that can be fed into the LSTM model. Common approaches include word embeddings (Word2Vec, GloVe) or using techniques like TF-IDF.

Sequence Padding: Ensure that all sequences have the same length by padding or truncating. LSTMs process sequences, and having consistent lengths is crucial.

Model Architecture: Design the LSTM model architecture. You can stack multiple LSTM layers, add dropout for regularization, and include a dense layer for classification.For multi-class classification (Liar dataset), the output layer should have the same number of neurons as the number of classes, and softmax activation function is often used.

IV. Results and Discussions

In this section, we describe the datasets that were used to track rumours using deep learning algorithms in the publications under consideration.

Liar Dataset: In total, 12.8K human-labeled brief remarks from politifact.com are included in the LIAR dataset, which is a well-balanced benchmark. It is divided into six categories of truthfulness: pants-on-fire false, barely true (half-true), substantially true (mainly), entirely true, and completely false (completely true).

In K6 and K12, around 12.8K annotated statements are utilised, with the latter containing the source of permission. There are statements that date back to 2007 and statements that date forward to 2016. According to Roy et al. [57], increasing the amount of labelled data and actual remarks from the speaker can assist in increasing the dataset quality. Semi-supervised models are also recommended for dealing with this issue. There are various ways to have a better understanding of how a person behaves when they speak, and one of them is to pay attention to what they say and how they express themselves.

Pheme Dataset: Despite the fact that PHEME is a dataset for feature identification, the developers of K1 and K2 and K11 utilised it to test a rumour detection system, according to the dataset description. For K11, around 5,800 tweets relating to five reported narratives have been compiled and annotated, according to the website. In addition, conversations on Twitter that were generated by false information are included in the sample. Tweets and public reactions to false news are included in this collection of exchanges. The Pheme dataset is used to train the classifiers and evaluated the proposed model, which they used to train and evaluate the baseline classifiers. They also discovered that when alternative feature engineering techniques are used on the PHEME dataset diverse events, the outcomes are dramatically different. For example, unlike previous studies based on the Pheme dataset, which did not balance their dataset by filtering out statements with fewer than ten tweets, K2 achieves precisely that.

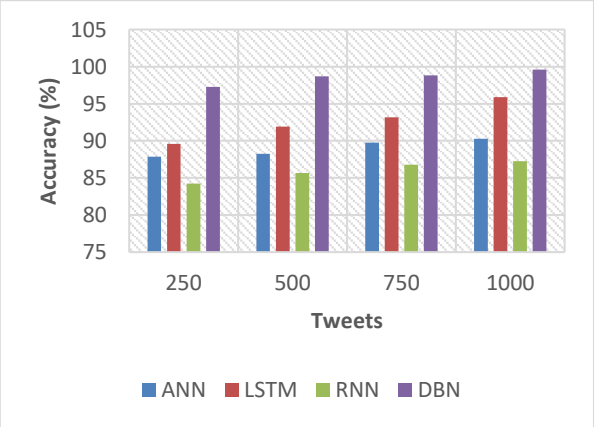

Figure 3: Accuracy

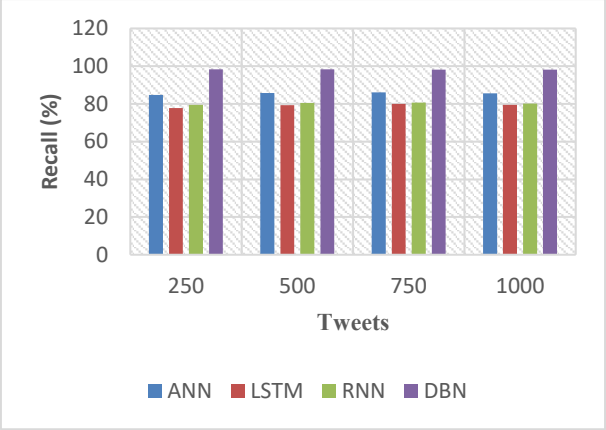

Figure 4: Recall

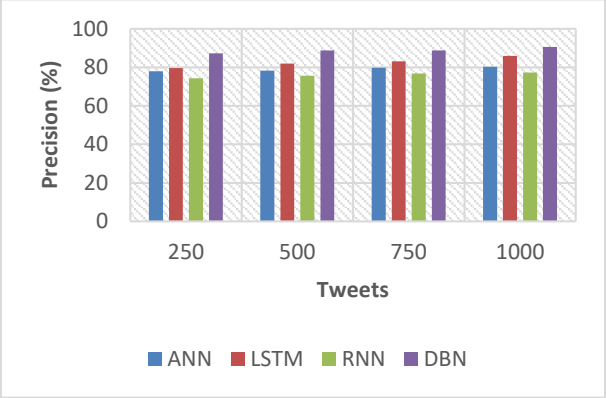

Figure 5: Precision

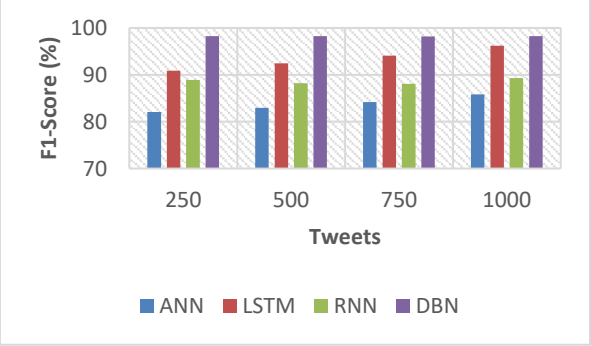

Figure 6: F1-Score

According to the standard machine learning approaches discussed above, when it comes to rumour detection, the recognition impact of a model with time series features is stronger than the recognition effect of a model without time series features. This shows that time series features can be added to a model to make it better at detecting rumors.

The performance of the RNN in rumour recognition outperforms that of the standard machine learning algorithms previously discussed. When compared to the existing deep learning techniques, the accuracy, precision, recall, and F1 values of the model have all increased by

more than 18%, indicating a significant improvement. When compared to the LSTM model, the RNN and DBN models improve accuracy, recall, and F1 scores by 1.3%, 5.4%, and 1.8%, respectively. Despite the slight increase in accuracy attained as a result of our approach, the number of input parameters and training rounds have both greatly decreased as a result of our approach. Manual extraction of subjective features, user features, and content feature modifications is also required for the LSTM algorithm to function properly.

Thus, when taking into account changes in sentiment polarity variables over numerous life cycles, the effectiveness of rumour identification may be demonstrated. The attention mechanism and the RNN are integrated on the basis of this premise in order for the input feature matrix to have varying levels of relevance. It is estimated that the accuracy rate and other assessment indicators have increased by 1.5–5%. When the DBN model is compared to the RNN model, the accuracy, recall, and F1 values of the DBN model have all improved significantly. Different time series have demonstrated that parameters such as sentiment polarity have a favourable effect on rumour recognition. The model accuracy and other metrics can be improved by more than 1.5% by including 20 additional pieces of information in the model. The four evaluation indices have also shown significant improvements. There is substantial evidence that simply increasing the quantity of input features through a simple spatial attention mechanism can boost the rumour recognition impact. Our goal was to demonstrate the beneficial influence of emotional polarity characteristics and the attention mechanism in distinct time series on the recognition of rumours, so we used these two operations on the RNN model to demonstrate this. Compared to the RNN model, there is a more than 2% improvement in accuracy, precision, recall, and F1 value by DBN.

V.Conclusions

In this paper, we model a rumour detection are developed using Deep Learning methods such as RNNs, DBNs, and LSTMs, with their accuracy assessed using accuracy, precision, recall and f1-score. When it comes to rumour detection, the results demonstrate that the proposed strategy is effective. In light of the uncertainty and significance, as well as a scarcity of readily available facts, the virtual social environment is rife with gossip. As a result, it is necessary to call into question the tangible nature of information. The goal of this work was to dismiss rumours on the Internet by employing a novel model for real-time rumour classification that learned a combination of integrated DBN and ant colony optimization-wrapper feature selection strategies in order to categorise rumours in real time. Whenever it is necessary to track down rumours, an effective model may be built by integrating text-based data such as the number of retweets with user-based characteristics. In the future, the hybrid model could be used to explore the processes that follow the rumour resolution pipeline. So, because text is used to look for rumours, context modelling can be used to improve the detection and rejection of false stories.

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