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Analysis of Rumour Detection using Deep Learning Methods on Social media

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Abstract:- Information and news collection via social media platforms is just one of their many useful functions. Nonetheless, they can inflict considerable harm because they can quickly propagate misinformation to thousands of users without proof. Several works of research have been explored recently to automatically regulate rumors by mining the text existing on the social media networks using deep learning techniques. This paper conduct a thorough assessment of deep learning techniques for detecting rumors on social media. The goal of this paper is to better understand current trends in the application of deep learning methods to the problem of identifying rumors. This analysis also includes a discussion of the difficulties researchers have encountered and a number of suggestions for further research on the rumor detection technique under scrutiny. This survey is helpful for researchers in the field because it describes in detail the performance matrices, dataset features, and deep learning model used in each work to enhance rumor detection accuracy.

***Keywords**:- Deep Learning; Socialmedia; Stance Detection; Machine Learning, Deep Learning, OSN, Rumour Detection.*

I. INTRODUCTION

Due to the viral nature of social media, it is crucial to monitor for and stop the spread of malicious rumors. In the absence of sufficient knowledge and confirmation to back it up, every piece of information that makes its way into the public realm is considered a rumor [1]. In times of crisis, it is widely believed and spreads like wildfire. It is undeniable that the economics of social media favour rumours, hate speech, pseudo-news, alternative facts, or false news [2, 3].

Online social networks (OSNs) are among the most frequently used services on the Internet. For the convenience of their customers, some businesses and people have developed rumor-checking resources including snopes.com, twittertrails.com, and factcheck.org. It takes a lot of time and resources for these websites to discover rumors because they rely on public reporting or manual verification. Inadequate content regulation is another factor in the spread of fake news on social media [4]. More than a third of popular events on microblogs contain incorrect material that spreads in seconds or minutes, according to a Chinese survey [5].

Facebook, WhatsApp, Twitter, and Instagram, among others, use tactics and tools specifically designed to detect rumors and increase online accountability in order to preserve the reliability of shared information. Artificial intelligence (AI), user feedback, and human content moderators all work together to create robust and accurate rumor detection rubrics. Yet users don't know the tactics and code of conduct, and moderators are stressed out by the volume of content and the difficulty of removing offensive comments. The aggressive virality of rumours is another source of online frustration [6]. The same false claim is often re-posted even after it has been proven to be false. Therefore, there is an immediate need for automated rumor debunking and measures to prevent their viral propagation.

There are typically four steps involved in determining the validity of a rumor and putting an end to its spread: spotting the rumor, following its progress, assigning it a position, and assessing its credibility [7].

- Rumour Detection: Here, a binary classifier is fed a continuous stream of postings, and the class labels each post as either rumor or non-rumor. It's essential for combating spreading rumors.
- Rumour Tracking: Social media is searched for postings that contain the input rumour's keywords or a sentence defining the rumour's subject matter. The resulting set of articles is then output.
- Stance Classification: Each rumor-related post that is generated by the rumor monitoring module is given a stance, such as "supporting," "denying," or "querying," by this module.
- Veracity Classification: This section generates the legitimacy of a rumor by combining the results of the first two sections with data from other web sources.

All of these stacks must be integrated and interact to form an absolute rumour resolution framework. It's possible that beginning with rumor detection will improve the quality of evaluations for later steps. The temporal feature of a rumour's lifetime [8] determines the events to which it is linked and how long those events last. A rumour's persistence over time may be indicative of its persistent and persistent nature, or it may be the result of a fresh development with no precedent.

One of the most effective methods for halting the propagation of false rumors is the timely identification of their veracity [9]. The intensity of an event is at its highest in the beginning stage, making early debunking crucial. Computationally intelligent models with the ability to learn and generalize can aid in automatic rumor identification. It is well-documented in the literature [1, 7] that several content-, user-, and network-based aspects are used. Identifying rumors in their earliest phases of spread is possible thanks to linguistic semiotic properties. Due to the nature of the medium via which rumors of breaking news are spread most commonly as trending stories and hashtags the simplest extractable textual elements of language can make a substantial contribution. There must be a way to automatically discover novel, latent aspects of natural language and their correlations within the incoming text if a news story or event is to be tracked in real time as it unfolds. The feature set and learning model are also essential components of automatic rumor.

In its most basic form, rumor detection is a text classification task that aims to determine whether or not incoming social media messages should be labelled as rumours [10]. Text categorization relies heavily on feature engineering, which is necessary for transforming raw data into a machine learning-friendly format. When classifiers incorrectly categorize rumors, the detection rate and accuracy of the system suffer. This is the main problem with text-based rumor detection.

In recent years, Deep learning techniques for rumour detection have been used successfully by researchers and achieved remarkable results. The input sequences are received serially by deep learning techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which then gradually extract features in multilayer training. The RNN used to construct the rumor detection algorithm would pick up on all the subtle changes in the context of relevant posts over time, learning all the hidden representations along the way. Based on the results of the studies, the RNN-based method is superior to others in its ability to detect rumors quickly and reliably. Extraction of relevant characteristics from an input sequence (contextual data) and shaping of high-level connections between significant features are also central to a CNN-based rumor detection system. By avoiding the curse of dimensionality and overfitting, deep learning algorithms can boost the classifier's accuracy and efficiency in a rumor detection system.

Here's how the rest of the article is laid out: Recent deep learning algorithms for rumor detection are presented in Section 2. The effectiveness of rumor detection methods is evaluated in Section 3. The future of the field is discussed and summarized in Section 4.

II. LITERATURE SURVEY

Using microblogging sites to learn continuous representations of events is an innovative approach proposed [11] for detecting rumors. The RNN technique, which is used in the proposed model, learns concealed representations to capture time-varying contextual information about relevant posts. As a first step, our technique transforms the incoming streams of microblog postings into continuous variable-length time series. To learn the whole set of discriminative features from the tweets' asynchronous propagation structure and produce a robust representation for spotting rumors, RNNs with various hidden units and layers for classification were employed. The method's poor efficiency became apparent when training on a large number of datasets.

In order to effectively detect rumors on microblogs, a novel Recurrent Neural Network (att-RNN) incorporating an attention mechanism was designed [12]. A trustworthy fused classification was generated by adding image features to the combined features of text and social context acquired using an LSTM network. Likewise, the LSTM's neuronal attention was drawn upon when fusing with the visual characteristics. This model uses the attention mechanism to capture the connections between images and words or social networks while aligning features. This approach to microblogging would record the full set of connections between a tweet's text, social context, and visual attributes. However, this method has low performance results than other existing methods.

In order to detect rumors on Twitter, researchers [13] created a neural rumor detection method employing recursive neural networks (RvNN) to integrate content semantics with propagation clues. This approach would use tree-structured RvNN to merge structure and content semantics for detecting rumors in microblog entries. By combining the structural and textual aspects indicating rumors from microblog postings, the two RvNN model versions (bottom-up and top-down tree topologies) were constructed to produce better integrated representations for a claim. However, this model had a rigorous data segmentation process in order to prepare the time sequence model.

For automatic rumor identification on Twitter, a deep neural network that relies on human attention was described [14]. This design incorporated author context and word focus to enhance categorization accuracy. To build the text representation, this architecture leveraged the word-level attention mechanism to give greater weight to pivotal terms. Individual authors' microblog posts were mined for extra context because of their potential to reveal their own writing styles and habits when disseminating material, both of which served as useful clues for determining whether the information being circulated was a hoax or not. The training time for this model increases when the input data contains several text patterns.

Rumor detection on OSN was addressed by presenting an unsupervised learning model [15] that combines RNN and Auto encoders to understand the typical actions of each users on OSN. Initially, the crowd wisdom was exploited to perform rumour detection in OSN. The detection performance was then improved by extracting new features from the suspicious microblogs comments. These attributes were trained using an RNN to learn to distinguish between rumor and credible posts over time. This model was built on the actions of single users, and it interprets rumors as outliers in the user's most recent posts. However, this model was a time consuming process as the learning phase takes more time to analyse and calculate all possible results.

In order to detect rumors on social media platforms like Sina Weibo, a novel Deep Recurrent Neural Network (DRNN) model was created [16]. An event-related stream of social media posts is received at the model's input layer, where a sequential coding method is used to extract user-specific post information. The model has eight layers. To do this, a normalization layer is added and two fully-connected layers as the first three hidden layers to the model. In order to capture the temporal dynamics of the post stream, the following two hidden layers were RNN layers. The likelihood that something is just a rumor is then output by a fully connected layer. However, this model was acquired with low training time.

In order to efficiently detect rumors in social media, a new model was presented [17] that makes use of Graph Convolutional Network (GCN) to collect user activity. It included the user encoder, the propagation tree encoder, and the integrator. By fusing user data with behavioural patterns, a user encoder was utilized to generate a GCN user representation graph. Using RNN, which links content semantics with spread indicators, the propagation tree encoder transformed the rumour's tree structure into a vector. A completely linked layer in the Integrator used the aforementioned module's output to make a determination on the veracity of rumors. Effectively capturing information concerning content, users, and rumor spread, this model accounts for all relevant aspects of rumor detection. However, this method has high computational complexity.

The LSTM network based models was presented [18] effectively for the rumors detection. Using forwarding contents, spreaders, and diffusion structures, this model would interact with CNN's pooling function to build efficient rumor identification models. For the purpose of content forwarding, word embedding was employed to obtain word presentation in forwarding remarks. These dynamic shifts in power, prestige, and popularity were recorded for disseminators to study afterwards. In the case of diffusion structures, the diffusion tree dynamics were created by switching between various node types within each diffusion layer and between layers. Yet, this technology for identifying rumors had a long delay before it could act.

For online rumor monitoring, researchers at [19] created a novel bi-directional graph model called Bi-Directional GCN (Bi-GCN). This technique was used to investigate both the top-down and bottom-up dissemination of rumors, two crucial aspects. This strategy would utilize a GCN equipped with a top-down directed graph of rumor spreading in order to study the patterns of rumor dissemination. Also, the bottom-up collection process was used to obtain the structural characteristics through the spread of rumors throughout communities. In addition, source post information was integrated into each GCN layer to amplify rumour's first influences. Yet, the GCN still had shallow structure, which could compromise the accuracy of the models.

A novel method was presented [20] for an automatic identification of rumors in social media which incorporates the word embedding and RNN algorithms. This approach was created to address the challenge of monitoring Twitter for the spread of false information related to breaking news. This system uses an innovative form of semi-supervised training, which integrates unsupervised and supervised training objectives, to identify rumors in the breaking news cycle. To avoid the cross-topic and out-of-vocabulary difficulty while spotting the breaking news rumor, a novel policy was employed to alter word embedding with the learning representations. However, this model doesn't model or remember things across time directly.

To learn the structure of social media, post dissemination, a Propagation Graph Neural Network (PGNN) was created [21]. Within a constrained number of time steps, the created PGNN structure iteratively alters the node representations by sharing data with their nearest neighbors along relation pathways. The original PGNN was expanded upon to provide Global Embedding with PGNN (GLO-PGNN) and ENS-PGNN (Ensemble Learning with PGNN). To further fine-tune the weight of each node, an attention technique was also used. However, it has many learning factors, making the process of fine-tuning those variables time-consuming.

To label the earliest stages of rumor events, the cutting-edge technique of Dual Convolutional Neural Networks (DCNN) was created [22]. This DCNN takes advantage of the information's inherent properties, such as its temporal, structural, and linguistic ones. Two CNNs were trained in parallel, with each receiving input from a vector representation of the collection of posts and embedded information pertaining to each event. The classification outcomes are independently extracted by the CNNs using language and temporal/structural variables. The classification output is then produced by the decision tree, which integrates the results from the CNNs. On the other hand, this model has low classification results compared to other existing approaches.

To accurately detect rumors on social media, a framework called KZWANG [23] was designed that combine text context semantic and propagation structural information. A focus technique was used to learn a textual semantic representation. To capture the global and local connections among all of the microblogs, reposts, and users in the source data, a GCN was implemented. A rumor detection classifier was trained using an organic combination of text semantics and heterogeneous graphs that spread. This method has better microblog propagation behaviour and contains more semantic and structural information. However, on extracting more semantic and structural information from the online social media, the level of noise was also increased.

Using a tweet-level Rumor Propagation based Deep Neural Network (RP-DNN) was proposed [24] as a novel hybrid neural network architecture for early rumor identification in Social Media. This architecture models the spread of rumors by combining the textual contents and social-temporal settings of input source tweets with a task-specific character-based bidirectional language model represented by stacked LSTM networks. In order to learn attentive context embedding across numerous context inputs, a multi-layered attention model was used. However, the efficiency and scalability of this model was not determined.

In order to detect rumors on Twitter, the Multiloss Hierarchical BiLSTM model with an Attenuation Factor was presented [25]. This model was able in extracting the deep information from small amounts of text by utilizing this hierarchical structure. The proposed model was segregated into position-level and event-level BiLSTM modules. These components allow the hierarchical model to quickly and efficiently learn the bilateral feature representation. Finally, a post-level attenuation factor was implemented to improve rumor detection precision. With only a few tweaks, this model might be put to use for detecting rumors both at the outset and as they spread extensively. The issue with this model is its delayed convergence.

It was proposed [26] to use parameter transfer in social media as part of a rumor detection strategy. To detect the rumors with constrained training data on social media platforms, a deep transfer model based on CNN (TL-CNN) was created. To fine-tune the model obtained during the transfer process, an adaptive learning rate update approach was created. This method is based on the stochastic gradient descent algorithm. This technique employs the standard detection model to transfer the model parameters learned from the polarity review data training set to the rumor detection model. In addition, a fine-tuning procedure for efficient rumor identification was carried out by adjusting a parameter of the fundamental detection model. However, this model has acquired with high training time.

To find these rumors, researchers [27] used a deep neural network (DNN) based feature aggregation modelling technique. Without feature engineering and domain understanding, this method would make use of the information included in the text feature of a social network event's propagation pattern. DNN successfully aggregated the text content feature and the temporal propagation features. In order to spread the time-related data, the propagation pattern feature modelling technique was created. After the event propagation cycle's volume and topology were removed, this temporal feature was built as a valid DNN input. However, this model required a lot of computing power.

A novel framework was presented [28] using deep representation learning called Participant Level Rumor Detection (PLRD) for the detection of rumor. PLRD uses multi-scale attributes of all users engaged in the diffusion process to forecast the specific post credibility like rumour or non-rumor. In order to quickly learn the social homophile for users, PLRD employs sparse matrix factorizations to embed the user-interaction network constructed from all propagation threads. A multi-hop graph convolutional layer and a bidirectional Gated Recurrent Unit (GRU) were used to train the fine-grained user representations. To represent doubts about the acquired features, PLRD uses a variation auto encoder. Assigning different weights to users and then combining their rumor representations was made possible by a user-level attention layer. Unfortunately, the database taken into account was minimal, and several user profiles had been deleted.

By combining deep learning (CNN) with filter-wrapper techniques like Information gain (IG) and Ant Colony Optimisation (ACO), a hybrid model was developed [29]. The embedding, convolution, activation, and down-sampling (pooling) layers make up the backbone of this CNN design, while the output layer houses a Bayesian classifier. Two sets of features were combined during training for this classifier. The CNN's learned features were used as input to the IG-ACO, which subsequently generated a feature vector with the highest possible accuracy. The Nave Bayes classifier was trained using this combined feature vector to make the rumor prediction. However, the convergence time was less in this method.

An approach [30] was created to identify the rumors using Attention CNN and Time Series of Context Data. At initially, event time series data was segmented using the Time Series (TS) technique. To get the polarity of the sentiment at varying time intervals, a standard SVM algorithm was created. Lastly, the text vector and the emotion polarity were merged to create the event characteristics that were sent into the CNN for rumor recognition. To further enhance the model's performance in rumor recognition, the spatial attention mechanism was applied to it, shifting the weighting towards more pertinent input variables. However, this method results with lower performance on large datasets.

Using the Long Short-Term Memory (LSTM) and Concatenated Parallel CNN, a New Hybrid Deep Learning Model [31] was created to detect COVID-19-related Rumors on Social Media (PCNN). This input layer was configured to accommodate social media posts with exceptionally long strings of text. The tweet was then fed into the subsequent layer after undergoing some pre-processing. This model makes use of three distinct pre-trained embedding layers, including word2vec, GloVe, and Fast Text model, to fine-tune the hyper parameters of each model. Separate word embedding was sent into the LSTM layer, and from there, each block produced a dimensional vector representing all word characteristics in the tweet. However, this required a lot of processing time.

The deep learning network based Simplified Aggregation Graph Neural Networks (SAGNN) was developed [32] for the rumor detection by capturing the twitter interactions in an effective manner. Layers of embedding, aggregation, and output were used to create this technique. The embedding layer recorded the vocab sizes of the vocabulary that included all terms in the considered twitters. In order to optimally capture the relationships between tweets and their offspring/parents, the aggregation layers make use of the learnable aggregation processes. In a neural network, the fully connected linear layer at the output performs a mean operation. However, the convergence time of this model is very slow.

It was proposed [33] to use a reinforcement learning algorithm to create a new model for Early Rumor Detection (ERD). Using a deep learning structure, a dual-engine rumor detection model was built to identify and categorize rumors based on tweets and replies. Also, a Twofold Self-Attention (TSA) mechanism was created to remove redundant information from both sentences and individual words. An LSTM-based ERD model was used in the reinforcement learning phase to learn the state sequence features and the optimization approach of the reward function for precise rumor identification. However, this model acquires low accuracy results compared to other existing methods.

A deep Neural Net was suggested [34] for the rumour detection by using the local and global structural information from twitter datasets. Every tweet and every reply to it were analysed using the Source-Replies relation Graph (SR-graph) technique. The SR-graph is a directed network where each node represents a twitter, the features of the nodes have been weighted as word vectors, and the edges reflect the relationships between the tweets. An SR-graph-based Ensemble GCN (EGCN) with a Nodes Percentage Allocation Mechanism was created to analyse and identify rumours. The effects of various word-embedding dimensions on various test indicators were then determined by analysing the derived structural features. This methodology, however, could only be used with modest rumor databases.

Using the linguistic characteristics from the short-text source tweets and the underlying temporal-structural information from the propagation trees of the source tweet, a novel deep feature fusion approach [35] was developed to detect the Twitter rumor. Context-aware linguistic features were extracted from the brief source tweet text using a pre-trained Transformer-based model. The tweet's "propagation tree" was embedded into the vector space as a sequential encoding approach. The purpose of the CNN design was to decode the propagation tree and extract temporal-structural information. This technique, however, calls for a massive amount of training data.

III. COMPARATIVE ANALYSIS

A comparative analysis is presented with their advantages and disadvantages of detecting different rumors based on deep learning methods which are compared and analysed, and their operational details are briefly explained in the above section. The merits and demerits of the above-mentioned methods for rumour detection are investigated in Table 1, and the best solution is suggested to overcome those drawbacks in deep learning-based rumour detection to obtain a better accuracy.

Table 1: Comparison of the performances in different deep learning techniques

No	Methods	Merits	Demerits	Datasets	Performance metrics
11	RNN Algorithm	Detect through temporal representation learning. It can detect long temporal dependent data	When training large number of datasets, slow performance was resulted.	Two microblog dataset, Weibo data is obtained from the Sina community management centre, and Twitter data is culled via an online rumor debunking service.	For twitter dataset Accuracy = 88% For Weibo dataset Accuracy = 91%
12	att-RNN, LSTM network and DCNN	This model has high detection rate and it effectively learns the joint features from all multiple modalities.	Low accuracy results for single modalities	The Twitter and weibo datasets are collected from MediaEval Verifying Multimedia.	For the twitter dataset, Accuracy = 78% For the Weibo dataset, Accuracy = 68%
13	Tree-structured model and RvNN	This model excels at identifying rumors in their earliest stages.	In order to properly build a time sequence model, this model necessitates a process of data segmentation.	Publicly available Two Twitter datasets namely Twitter15 and Twitter16.	For the Twitter 15, Accuracy = 72.3%; F1-Score = 72.8% For the Twitter16, Accuracy = 73.7%; F1-Score = 73.7%
14	Attention-based ensemble Deep neural architecture and word-level attention mechanism	This model was effective to train even small rumor dataset.	High training time due to extensive text patterns	Information was compiled from the websites snopes.com and emergent.info, which are noted for their ability to debunk urban legends.	For rumour and Non – rumour class Accuracy = 82% F1-Score = 81.15%
15	RNN and variant AE	It was more efficient to utilize this approach to construct the learning model for a single user than for	It was a time consuming process.	SinaWeibo dataset collected from Weibo Community Management Center	Accuracy = 92.49%; F1 measure = 89.16%.

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		all users collectively.			
16	DRNN	This DRNN model provides better detection for sparse nature dataset	This model had a high training time.	Sina Weibo, and Publicly available Twitter dataset	Accuracy = 92%; Precision = 94% Recall = 89%; F1-score= 91%
17	GNN and GCN	Even on the larger dataset, the model provides the best performance results	High computational complexity	Twitter15 and Twitter16 are two openly accessible Twitter datasets. The 1,381 trees in the Twitter15 dataset are propagation trees, and 276,663 users. There are 1,181 trees of propagation on Twitter16, and 173,487 users.	For the Twitter 15, Accuracy = 75% For the Twitter16, Accuracy = 77%
18	LSTM network	This model provides better results for long temporal dependent events effectively	High detection time	The 1623 rumors and 1756 non-rumors that make up Sina Weibo's dataset.	The accuracy of rumour and Non-rumour class detection = 94.8% and 94.9% respectively.
19	Bi-GCN	This model has high-level tree structures for an early rumour detection	More time complexity	Three real world datasets like Weibo, Twitter15 and Twitter16	Accuracy of Bi-CN on Weibo dataset for false rumour = 96.1% True rumour = 96.1% Accuracy of Bi-CN on twitter 15 dataset for false rumour = 86% True rumour = 93% Accuracy of Bi-CN on twitter 16 for false rumour = 87% True rumour = 94%
20	RNN algorithms and semi-supervised training model	Low computational complexity	This system was unable to model memories over time.	PHEME dataset	The accuracy of rumor class, Non-rumor class and both classes are 81%, 76% and 78% respectively.
21	PGNN GLO-PGNN ENS-PGNN	The storage space was comparatively less than other methods	Fine-tuning variables was a tedious process	PHEME datasets	Macro-F1 score (GLO-PGNN) = 75.3% Mirco-F1 score (GLO-PGNN) = 76% Macro-F1 score (ENS-PGNN) = 75% Mirco-F1 score (ENS-PGNN)= 74%
22	DCNN	Lower detection time	Low classification results for complex interacted datasets.	The datasets are collected from Twitter15, Twitter16, Twitter17 and Twitter18 social media sites	For the Twitter 15, Accuracy = 88.6% For the Twitter16, Accuracy = 88% For the Twitter16, Accuracy = 90% For the Twitter16, Accuracy = 87%
23	Attention mechanism and GCN	High detection capability for sparse features and has	The noise level was increased due to the extraction of more semantic and	Twitter15, Twitter16, and the Sina Weibo are three social media datasets	For the Weibo, Accuracy = 95% For the Twitter 15, Accuracy = 90%

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		very low computational time	structural information on social media.		For the Twitter16, Accuracy = 90%
24	RP-DNN, LSTM networks and Multi-layered attention model	Detect even unseen rumor events effectively	Efficiency and scalability was not determined properly.	PHEME, twitter 15 and 16 datasets.	Overall accuracy detection rate = 80.4%; F1-score = 81%
25	Multiloss Hierarchical BiLSTM model with an Attenuation Factor	This approach has broad relevance for both early and widespread rumor detection because it represents any post or event text with a fixed-length vector.	Slow convergence problem	Two datasets from PHEME 2017 and PHEME 2018.	For the PHEME 2017, Accuracy = 92.6% For the PHEME 2018, Accuracy = 91.9%
26	TL-CNN and Adaptive learning rate updating method	This model achieves better performance for both sparse and dense datasets.	High training time	Yelp Polarity (YELP-2) dataset and Five Breaking News (FBN) dataset	Accuracy = 87.3%; F1-Score = 82.5%
27	DNN and Propagation pattern feature modelling method	Low detection time with accurate results.	High computational cost	Dataset of 2313 rumor samples and 2351 non rumor samples, available to the public.	Accuracy = 94% was found for early rumor and non-rumor detection.
28	CNN, Filter-wrapper approach like IG and ACO	This model is suitable for very high dimensional and spatially variant datasets	Very fast convergence time.	PHEME Dataset with different events like German wings crash, Charlie Hebdo Ottawa shooting, Sydney Siege, Ferguson unrest	The accuracy of German wings crash = 76.7%; Charlie Hebdo = 85.6%; Ottawa shooting = 74.9% = Sydney Siege = 74.0% Ferguson unrest = 87.4
29	PLRD, Multi-hop graph convolutional layer and bi-directional GRU	Increased model generalization with less training time.	Limited database with no longer accessible of client profiles.	Twitter 15 and Twitter 16 datasets collected from Twitter API	For the Twitter 15, Accuracy = 93.4% For the Twitter16, Accuracy = 87.5%
30	Attention CNN and Time Series of Context Information	This model takes less time to train from data.	Lower performance on larger datasets	Two datasets like Datasets 1 collected from Weibo data set with sentiment labels Datasets 2 extracted from the Sina community management.	Detection Accuracy and F1-Score of this model = 8.82%
31	Hybrid Deep Learning Model, LSTM and PCNN	This method automatically selects important features for achieving high detection rate.	High computational time	ArCOV-19 dataset which contains Arabic tweets about the COVID-19 pandemic situation.	Detection accuracy = 86.37%
32	SAGNN	Less computational complexity	Fast convergence time	Twitter15 and Twitter16 datasets	For the twitter 15 dataset, Accuracy = 85.7%; F1-Score = 85.9 For the twitter 16 dataset Accuracy = 76.4%; F1-Score = 74.4%
33	Reinforcement learning algorithm, Dual-	This model was efficiently optimized and practical to	Low accuracy results for large size datasets	PHEME Dataset	Accuracy = 75%; F1-Score = 75%

	engine rumor detection model and DRQN	detect the rumor with limited data.			
34	Deep Neural Net and EGCN	EGCN was more effective for identifying complex correlated interactions in twitter dataset	Suitable only for small rumor datasets	PHEME datasets has five event topics like Charlie Hebdo, Sydney Siege, Ferguson, Ottawa shooting, German wings crash events	Precision for Charlie Hebdo, event = 88.1% Precision for sydney Siege, event = 82.1% Precision for ferguson event = 80% Precision for Ottawa shooting event = 72.5% Precision for Germanwings crash event = 70.2%
35	Deep feature fusion method, Transformer-based model Sequential encoding method	This model is suitable for large dataset and provide best performance for large corpus Twitter dataset	Requires large number of training data.	Two Twitter datasets like Twitter15 and Twitter16 are adopted for the rumour detection.	For the twitter 15 dataset, Accuracy = 86.2%; F1-Score= 83.8% For the twitter 16 dataset, Accuracy= 89.6% F1-Score= 86%

IV. PERFORMANCE EVALUATION

Also, the accuracy and F1-score graphs for RvNN [13], Attention-based ensemble Deep Neural Architecture (AE-DNA) [14], RP-DNN [15], SAGNN [32], and TL-CNN [27] are compared to those for the Deep Feature Fusion approach for Rumor Detection (DFFRD) [35].

$$Acc = \frac{TP+TN}{TP+TN+FP+FN}$$

$$F1 - score = \frac{2\times Precision \times Recall}{Precision + Recall}$$ where

$$\text{Precision} = \frac{TP}{TP+FP}; \ \text{Recall} = \frac{TP}{TP+FN}$$

In Fig. 1, the accuracy values for DFFRD, RvNN, AE-DNA, RP-DNN, SAGNN and TL-CNN techniques are given. From the above figure, it is analysed that the DFFRD is 21.5%, 17.2%, 11.4%, 9.2% and 2.6% is greater than RvNN AE-DNA, RP-DNN, SAGNN TL-CNN methods. So, it is proved that Deep Feature Fusion approach for Rumor Detection (DFFRD) technique has the maximum accuracy than the other rumour detection techniques.

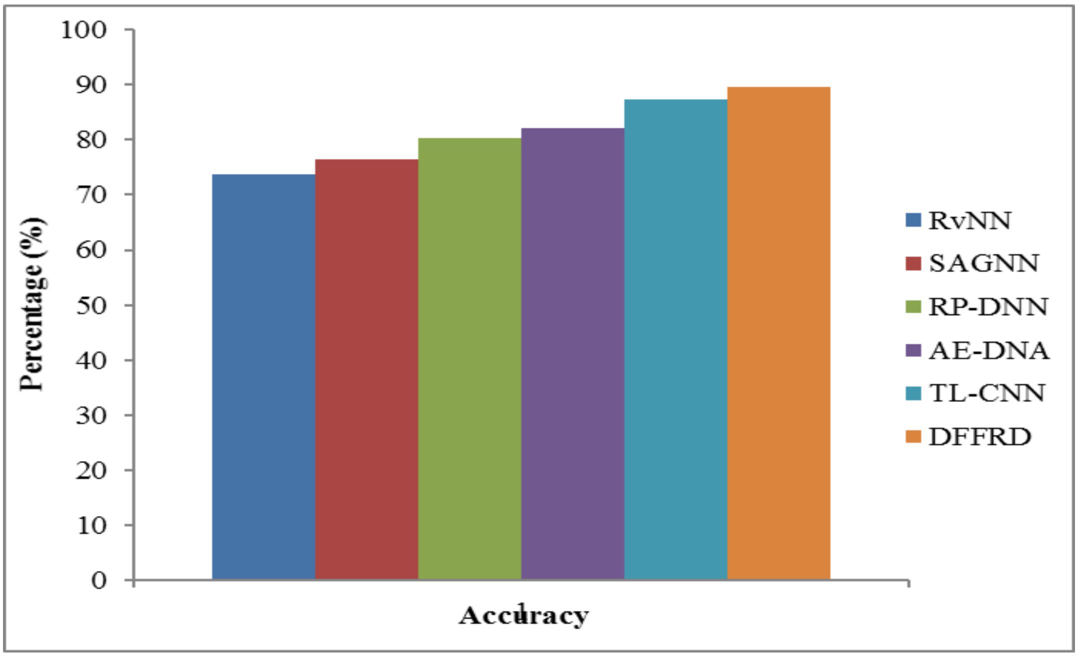

Fig. 1: Comparison of Accuracy

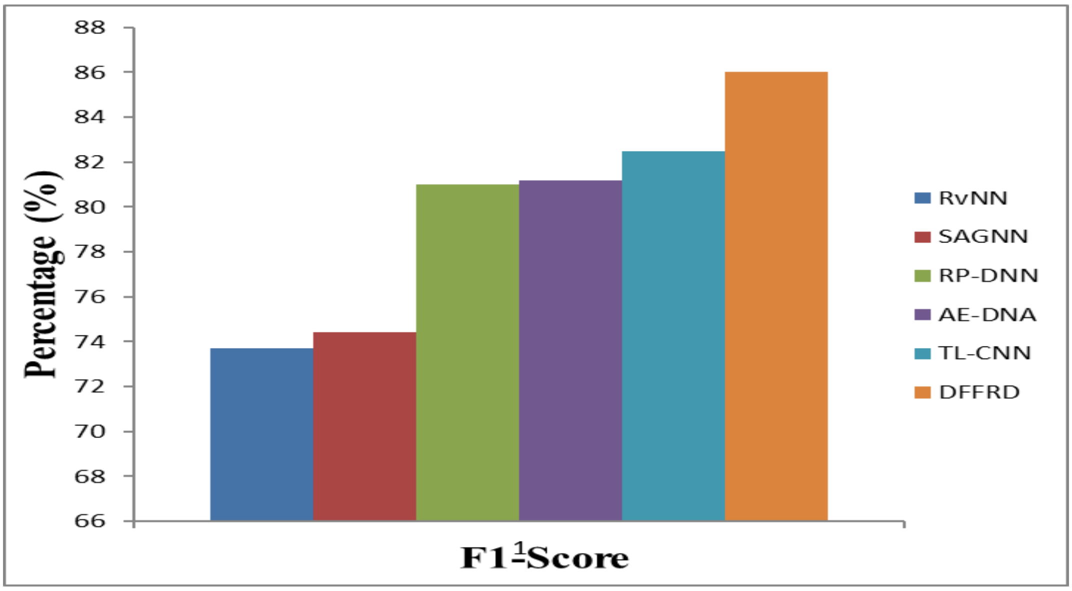

Fig. 2: Comparison of F1-Score

In Fig. 2, the F1-Score for DFFRD, RvNN, AE-DNA, RP-DNN, SAGNN and TL-CNN techniques are given. From the above figure, it is analysed that the DFFRD is 16.6%, 15.9%, 6.17%, 5.9% and 4.2% is greater than RvNN AE-DNA, RP-DNN, SAGNN TL-CNN methods. So, it is proved that DFFRD technique has the maximum F1-Score than the other rumour detection techniques.

V. CONCLUSION

In this survey, a detailed comparative study on rumour detection using several deep learning methods is presented. From this comparative analysis, it is clearly observed that all researchers have experienced the different methods for rumour detection activities on rumour detection-based deep learning system has greatly encouraged research on social networks in order to avoid certain damages in their functions. This study provides a review of the most up-to-date methods for identifying rumors in online communities. The advantages and disadvantages of using these methods to effectively detect rumors on social media have also been examined. Researching other deep feature information, such as user profiles and comments, will be enhanced to promote realistically useful rumor detection in the future.

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