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EMPIRICAL ANALYSIS OF RUMOUR DETECTION USING SUPERVISED CLASSIFIERS

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ABSTRACT

Unlike word of mouth, a local newspaper or radio broadcast, the internet's reach is way beyond the control of any person, group of individuals or organizations. It takes seconds for rumours to spread and cause trouble for the people or governments involved, sometimes taking an ugly turn. In order to curb any malice/chaos arising due to false rumours, rumour detection models can be an aide. There has been development using Machine Learning classifiers, but it has been observed that they may not be the most-high performing and do not work well with complex datasets. There are Deep Learning (DL) models too that have been probed into this niche, but mostly for specific use cases using redundant, traditional techniques. Also, performance of the existing models can be improved. Through this work the authors implement supervised classifiers for rumour detection like K-Nearest Neighbor, Support Vector Machines, Random Forest and Passive Aggressive Classifiers to optimize, analyze and compare the performance. By using count vectorizer and TF-IDF vectorizers with accuracy score as performance metrics, it is determined which classifier provides the best results. A Bidirectional Long Short-Term Memory (BiLSTM) model that can outperform the redundantly used DL models and further probe if deep neural networks are a better approach for rumour detection is also implemented. Its results are compared with previously used techniques; namely Single LSTM, Hybrid Convolutional and Recurrent Neural-Networks, Recursive Neural-Network and CNN-BiLSTM. Two benchmark datasets: Pheme and fake news dataset have been used for the deep and machine learning classifiers respectively.

Keywords: Machine Learning (ML), Bidirectional Long Short-Term Memory (BiLSTM), Deep Learning (DL), Rumour Detection, Convolutional Neural Network (CNN)

1. INTRODUCTION

Since the inception of social media and the disruption that it has resulted in, the amount of data generated every minute is humongous. Although it has proved to be a boon and a major source of awareness, information as well as means to ensure connectivity with people from across the globe, it does come with its own set of cons. Like every other medium, social network and the internet in general are home to individuals and organizations with malicious intent, including people who resort to click baits and misinformation in order to gain clout, money or maybe just a laugh out of. Within the current scenario, this culture of "spreading rumours", irrespective of the reason (intentional or unintentional) has become rampant. It could lead to loss of business, maligning identity, create chaos, confusion, misinformation etc. 'Rumours' and 'Fake news', although frequently used interchangeably, differ in the sense that rumours deal with information that are doubtful or unverified in nature whereas fake news is mostly fabricated (Kumar et al., 2019). The latter is completely made-up and might be outrageous enough to be gauged as being untrue, which might not be the case with rumours (Bondielli et al., 2019).

Thus, the primary focus of this research is probing the recent work in rumour detection and to identify the research gaps, implementing rumour detection using both machine and deep learning classifiers on two benchmark datasets to infer which techniques provide better results and as DL is still in its nascent stage - with machine learning models being more in application, we compare and analyze results of both. ML models have several limitations pertaining to time, cost and human labor involved thus DL models are being researched upon for more accurate, faster systems that can easily handle big data.

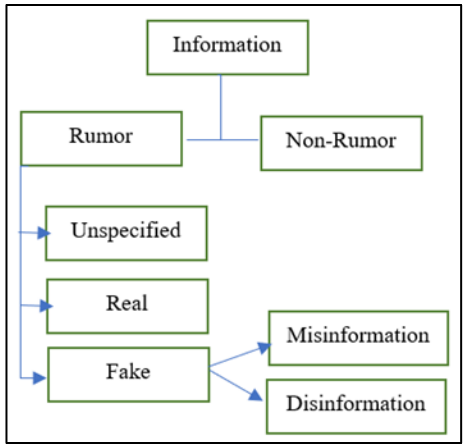

Figure 1: Rumour Classification

Through this work the authors implement classifiers based on machine and deep learning which are optimized through tuning and adjusting of parameters, data inclusion and better pre-processing so that the results could prove to be better than the pre-existing models and of higher accuracy (Pathak et al., 2020). The Fake (potentially unreliable) and real news dataset (data.csv) and Pheme datasets have been used for the same (Li et al., 2019). Since the Pheme dataset is comparatively less balanced, larger in size and overall, more complex than the fake news dataset, we use it for the Deep Learning based implementation and analysis. A review of the various machine as well as DL-based approaches that have been used in the recent past (primarily the last five years) was done and a glimpse into the future scope of these approaches was also taken, including where they lacked and a comparative analysis to figure out the main reasons for it. The authors also look at the performance of all these classifiers and plot confusion matrices for the ML techniques and made use of the Bidirectional LSTM technique primarily, to compare its performance with the existing results of Hybrid Convolutional and the Recurrent Neural Networks-LSTM (Ajao et al., 2018), single (attention-based) LSTM (Singh et al., 2020), Recursive Neural Network (C P et al., 2019) and CNN-BiLSTM models (Rani et al., 2021). The implementation of the supervised classifiers-based rumour detection system incorporates Random-Forest, Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Passive-Aggressive Classifiers (PAC). The final results are concluded in the results section.

2. LITERATURE REVIEW

2.1 Using Machine Learning for Rumour Detection

As mentioned in the previous sections, over the years we have observed contributions to this field and several researchers have come up with models based on machine learning techniques to combat rumours. Every subsequent research work has tried to be more accurate and optimized than its predecessor. We have seen models based on supervised learning classifiers including Gaussian Naïve Bayes, Random Forest, Support vector machines, K-nearest neighbors and logistic regression (Hassan et al., 2018). A common conclusion through most of these works was that naïve bayes performed better on data samples that were smaller in size (Kotteti et al., 2019). The accuracy might come out to be greater than the other classifiers but might not be the best judge of a technique's applicability for real systems as the size of data they have to deal with is immense. It is difficult to see propagation patterns when data is less or samples are scattered (imbalanced distribution). These might lead to results being unreliable (Parab, 2019). In a number of cases random forest proved out to be the overall best classifier (Hassan et al., 2018) (Mahmoodabad, et al., 2018) (Sicilia et al., 2018). In case of support vector machines, the usage of Radial Kernel in place of Radial Basis Function (RBF) gave slightly optimized results. Even for K-nearest neighbor classifier, tuning of parameters helped in achieving better results (Parab, 2019).

2.2 Using Deep Learning for Rumour Detection

Some prominent and most recent advances in DL-based detection models for rumours are listed in the following table:

Table 1: Review of recent Deep Learning-based research

S. No.	Author(s)	Techniques/Algorithms Applied	Dataset used	Outcome/Efficacy	Remarks
1.	Asghar et al. (2021)	LSTM with Convolutional Neural Network	Pheme rumour dataset which has about “5800” tweets of the breaking news events.	86.12% accuracy of model	ML classifiers like KNN, DT, Random Forest, LR and Naïve Bayes were experimented.Variants of DL-based models: LSTM, CNN, LSTM-CNN RNN were also implemented.
2.	Kumar et al. (2021)	Convolutional-NN and filter-wrapper technique, along with a optimized Naïve Bayes classifier	Pheme rumour dataset of rumours and non-rumours	0.732 Superior F1 using the proposed classifier	CNN was used for automatic learning that was feature based.IG-ACO for selection based on features.Naïve Bayes for classification.
3.	Al-Sarem et al. (2021)	LSTM as well as Concatenated Parallel Convolutional NNs (PCNN)	ArCOV-19 dataset	Detection accuracy reached 86.37%	Experiments were conducted using 3 static word embedding models: word2vec, GloVe, and FastText. DL methods can extract informative features directly from textual content without human assistance unlike ML approaches.
4.	Lv et al. (2020)	Comment sentiment and CNN-LSTM	Crawling of Fake Weibo info (Microblog and Comment dataset)	92.66% accuracy of model (limited to specific areas)	Method compared to ML methods such as NB, SVM, and common DL model.CNN-LSTM constructed gives the best effect in the comparative experiments.
5.	Zhou et al. (2020)	CNN-LSTM and Soft max classifier	Weibo platform	Accuracy and time efficiency were improved compared to NN model that is single.	For feature classification: Softmax LSTM prevents loss of memory and gradient exploding problems.
6.	Huang et al. (2020)	Spatial Temporal Structure-NN (STS-NN)	Two twitter benchmark datasets which are public:	STS-NN model better than baselines.	Message propagation has characteristics of both temporal and spatial structure.

			Twitter15 and Twitter16		Prior techniques modelled both separately. This paper addressed this issue.
7.	Guo et al. (2020)	Deep transfer model and adaptive parameter tuning method	Yelp Polarity (YELP-2) and Five Breaking News (FBN)	Model can significantly improve accuracy, can have several real-world applications.	Proposal of a learning rate tuning technique which is adaptive in order to avoid the (-) ve transferring.
8.	Singh et al. (2020)	Attention-based LSTM network	Pheme dataset	0.88 F1-score found	Performance of several ML and DL models compared. Hybrid feature set is created by from text using LSTM.
9.	Lin et al. (2019)	Hierarchical recurrent convolutional-NN	Twitter and Sina Weibo.	Solution provided better results than existing ones.	RCNN-Feature Attention network to learn the contextual representation info, and the BiGRU network which has a feature attention layer in order to learn time-period information.
10.	Huang et al. (2019)	Graph CNN	Twitter datasets 15 and 16	Exhibits improved performance than prior methods.	The model consists of three modules: integrator, user and propagation-tree encoder.
11.	Do et al. (2019)	Dual RNN	Weibo and Twitter datasets	Achieved better results compared to various pre-existing models	Propagation pattern is an imp factor in detection. Padding and scaling in order to improve i/p features of the model is designed.
12.	Han et al. (2019)	Data Augmentation (DNN model)	PHEME (6392078), Crisis LexT26, Twitter event datasets, Sem Eval-2015 task-1 data, CREDBANK, SNAP data	Augmented training data helps train Deep-NNs through prevention of overfitting, which further improves model generalization	For future it is to be noted whether data augmentation creates a bias while detecting the similar sort of rumours.
13.	Chen et al. (2019)	Attention-Residual based network with Convolutional Neural Network	Twitter dataset called Tree and using query method using keywords	87.0% accuracy was achieved on TREE dataset	The attention model with residual network was inculcated for utilizing rumour detection for the first time

				and an accuracy of 80.7% on DOT data	
14.	Ma et al. (2018)	User attention-based CNN model	Twitter datasets, namely, Twitter15 and Twitter16 by Ma et al.:	Performance largely improved as compared to prior baselines	A bottom-up and a top-down model which is tree structured and based on recursive NNs is proposed.
15.	Chen et al. (2017)	Recurrent Neural Networks and Autoencoders	Rumours on OSN	Obtained accuracy of 92.49% along with a F1-measure of 89.16%	View rumour detection as a task of anomaly detection. Crowd wisdom is also exploited. The model is based on unsupervised learning and thus does not need labelled data for training.

It is also inferred that adding dropout layers can help in avoiding the overfitting of models in deep learning-based rumour detection models. Also, if the batch size and epochs are tuned well enough, then significantly better results can be achieved (Parab, 2019).

2.3 Why use Deep Learning?

The sophisticated nature and ability to deal with complex patterns is what helps set apart deep learning models. Although there can be arguments that these models can take longer to train, but even though training is intensive and long, it helps reduce the testing time (Chalapathy et al., 2019). They are overall much more robust and better at handling real time big data. There are majorly three major kinds of models that this niche categorizes into, namely- discriminative, generative and hybrid models. While recurrent, recursive and convolutional neural-networks fall under the discriminative category, LSTM along with combinations of the above-mentioned models fall under the hybrid category (Islam et al., 2020). Generative models have been implemented for spam, fake news and tracking other malicious activities but their direct contributions in rumour detection using DL, although present is still tricky.

2.4 Importance of Rumour Detection and existing limitations

The common notion is that “fake news” is more problematic and injurious to society and individuals, especially due to its rampant rise in the recent years. Rumours, on the other hand are seen as lesser of the two evils and considered to have fewer consequences. There was a time when rumours were spread through individuals directly and their reach was fairly limited. But with social media and platforms like Twitter, Instagram, etc. the reach is beyond what we can fathom (Alzanin et al., 2018). Also, the anonymity associated with these platforms paves the way for miscreants to indulge in spreading them without the fear of any repercussions. Rumours have the power to even influence consumer purchasing behavior and marketing if leveraged accordingly (Abdelkader et al., 2018). They can increase and instill conflicts, victimization and even polarization of groups, if remained unchecked. Through social media and the internet, even a harmless gossip can be turned into full-fledged misinformation and chaos within few moments. They could lead to anxiety and other consequences like reduced productivity and creativity. Opinions can be made and jeopardized.

Therefore, it is extremely crucial to have effective means to tackle rumours before they are converted into irreversible damage. As technology evolves, so do the harm-doers. In order to stay with the times, it is important to analyze the mistakes and limitations of earlier mechanisms and optimize the pre-existing models. Some of the research limitations and gaps observed upon reviewing the
previous works were:

- On the basis of the literature review, it was observed that although significant studies and development are taking place in the domain of rumour detection, majority of the quality and well-established work is in the Machine Learning domain only. It should also be noted that deep learning models are being devised for dealing with rumours, but the amount of work that is currently present can be improved further to increase efficiency and accuracy. From the publications and research work the authors reviewed, which have been implemented using benchmark datasets and using latest techniques, it was found that only 2 of the models could provide an accuracy greater than 90%. Also, these results were limited to specific datasets. Although the performance is constantly being improved than its predecessors, there is a need for better and optimized models that provide higher accuracy rates.
- It was also observed that due to feature engineering and the heavy pre-processing required, traditional machine learning techniques consume more time and require more labor in the form of human intervention. Even after this, a few features might not be available, adequate or unextractable. In comparison to ML models, the ones based on deep learning have a stronger learning capability and are more adept to dealing with huge amounts of data, which is a must nowadays. From the research work above, it was also deduced that some datasets have been tweaked and reduced in size for specific use cases and thus training of the models does not provide very high performance.
- No proper treatment of outliers and missing data could also be a reason for reduction in quality. Technology and science are developing every minute, and with time the gradual shift towards super intelligent systems is inevitable. Thus, the need for designing and developing reliable systems that can be helpful in the years to come is likely. We have models based on LSTM, RNNs, CNNs, etc. but their scope and efficacy are still questionable and limited to specific niches. We need more tools that are capable of making the digital space more secure.

3. IMPLEMENTATION DETAILS

While detecting rumours, the most significant aim is to conduct the detection process as soon as possible so that necessary interventions can be made in order to curb misinformation or confusion. Based on previous studies as well as in regard to the requirements of the near future, a model based on Deep Learning is built so that the limitations of Machine Learning that have been discussed in the previous sections can be overcome. In order to deduce the capability of this technique, we computed performance of this model with regards to previous works (by other scientists and researchers) that were based on Hybrid CNN and RNN, single (attention-based) LSTM, CNN-BiLSTM and Recursive Neural Network on the same dataset. For this paper, the deep learning based Bidirectional (double layered) LSTM approach was used. The process flow for this approach is as represented in Figure 2.

The reason why BiLSTM would provide better results is because single layer LSTMs do not take context into consideration. This approach on the other hand will be able to handle the data in both forward and a reverse (backward) direction (Kumar et al., 2020). LSTMs are types of and a kind of artificial RNN that give the best results and more controllability, especially for text-based classification. CNNs work well with visualization and larger datasets. Although it is believed that CNNs have an edge over RNNs, for textual form of data, RNNs and more so LSTMs seem to be the better option.

To find out which technique would be able to give the best results and compare the results with ML based solutions forms the crux of this research work. The ML-based classifiers (Random-Forest, KNN, SVM and Passive-Aggressive Classifier) are being implemented to test the performance of each on the fake (potentially unreliable) news dataset for rumour detection. Python 3.9 was used as the language for development, Jupyter notebook as the platform for implementation of the models and the benchmark, publicly available Pheme (platform-Twitter) dataset: - Pheme dataset for rumour and non-rumours was used for the Deep learning model (Zubiaga et al., 2016).

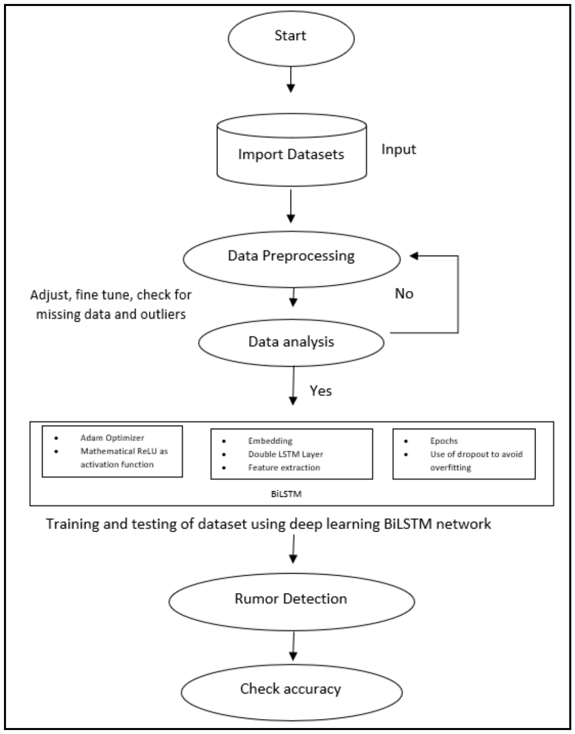

Figure 2: Flow of Implemented Deep Learning Technique

The reason python has been proposed is because of the abundant libraries it provides, which makes it the ideal choice for all deep and machine learning projects. For the Machine Learning analysis, Fake (potentially unreliable) news dataset (data.csv being the final version after treating the data) was used. The machine learning-based implementation of the project can be understood using the process flow given in Figure 3.

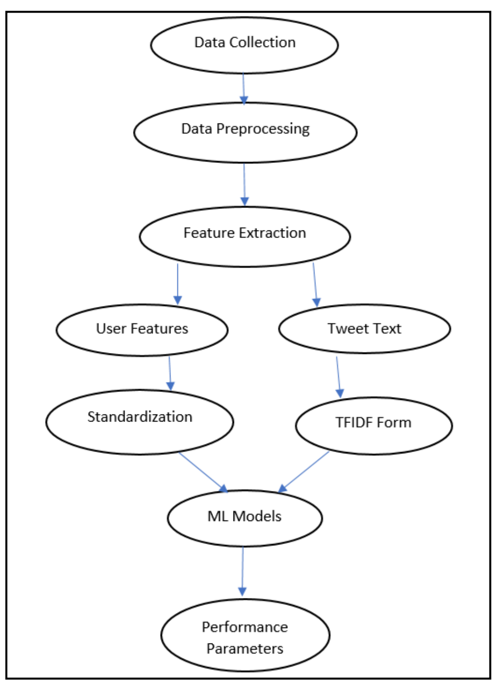

Figure 3: Flow of Implemented Machine Learning Techniques

3.1 Data Pre-processing

The Pheme Dataset is a benchmark dataset that contains tweets breaking news tweets from five major events. They are categorized as rumours and non-rumours. After pre-processing and removing of unwanted data like hashtags, stop words, etc. and further conducting the processes of stemming and tokenization on the dataset, we are left with a total number of tweets equal to 5802 (Li et al., 2019).

The Fake news dataset ("data.csv") was used for implementing the machine learning based detection models. It contains a list of news articles along with their URLs, headlines and body. The dataset consists a total of articles 4010 in number. They are labelled as 0 and 1 for rumour and non-rumours respectively. Here again the data was cleaned and pre-processed using the same techniques as the Pheme dataset and the train: test ratio was kept at 25:75 respectively. The count and TF-IDF vectorizers were used to get rid of any words from the dataset (article) that occurred >60%. The URLs for both the datasets are:

- Pheme dataset for rumour and non-rumours: "https://figshare.com/articles/dataset/PHEME_dataset_of_rumours_and_non-rumours/4010619"
- Data.csv dataset that contains reliable and potentially unreliable news excerpts: Acquired from "https://github.com/" rumour detection repository (Also available on Kaggle at URL: "https://www.kaggle.com/c/fake-news/data" – original source, before tweaking).

3.2 Heatmaps for the Pheme Events Tweets

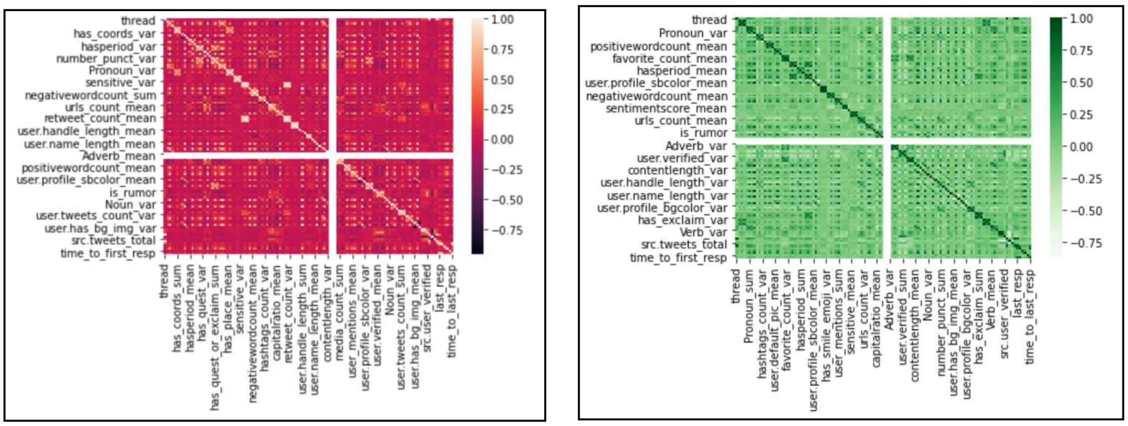

Figure 4: Heatmaps for Charlie Hebdo and Germanwings Crash respectively

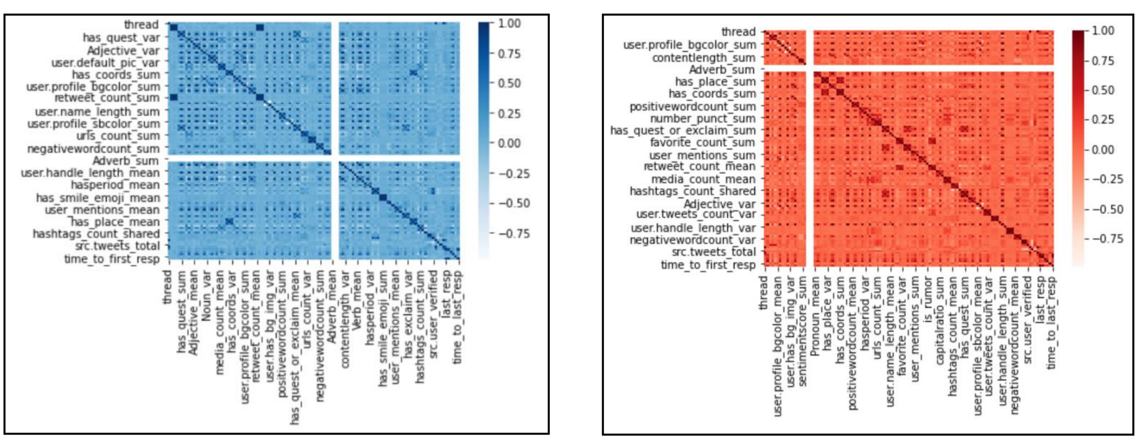

Figure 5: Heatmaps for Ferguson and Ottawa Shootings respectively

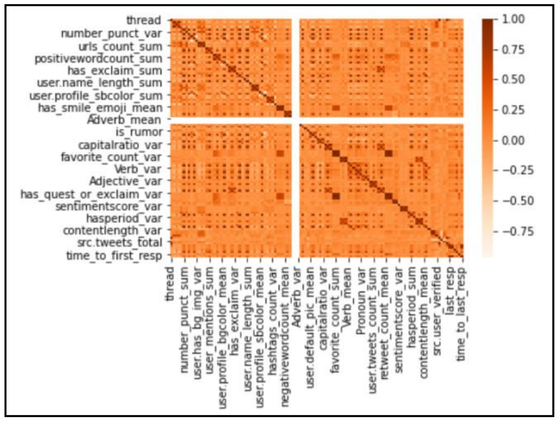

Figure 6: Heatmap for Sydney Siege

For the deep learning based (BiLSTM) implementation, since it is a bidirectional LSTM based approach, there is a use of two layers of it, i.e., in both the forward and reverse directions. For optimization, the following parameters have been used (with a 0.2 dropout layer in order to avoid overfitting):

- Adam Optimizer: It is an optimizer that depicts an adaptive nature and is frequently used in deep learning or neural network-based models (Brownlee, 2017).
- ReLU Function: Due to its ability to train easily and provide better performance, Rectified Linear Activation Function is widely preferred (Brownlee, 2019).
- SoftMax function: It provides the feature of non-linearity to a model or network. It's usually used as the last or output activation function (Saxena., 2021).

4. RESULTS AND DISCUSSION

The following confusion matrices were plotted to represent the results of the ML classifiers. Their results will further be discussed and compared.

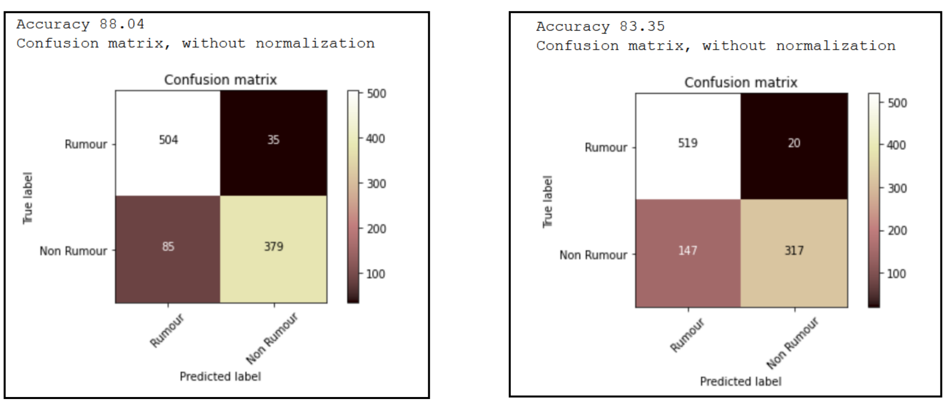

Figure 7: Confusion Matrices for Random Forest: with Count and TF-IDF vectorizers respectively

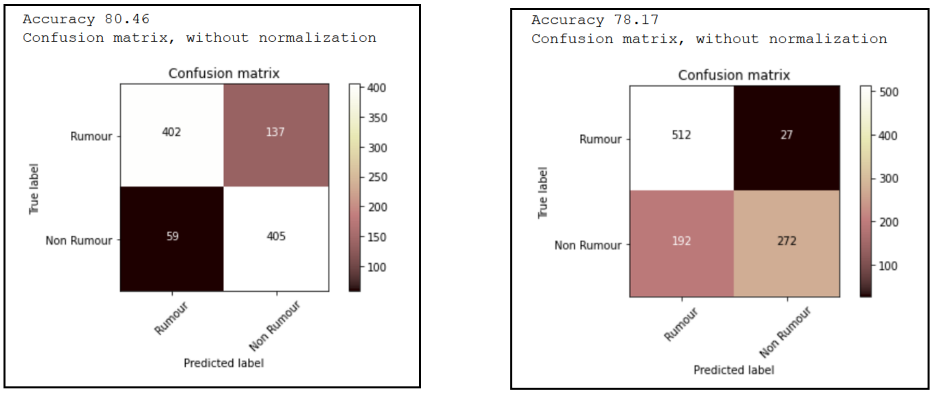

Figure 8: Confusion Matrices for KNN: with Count vectorizer and TF-IDF vectorizer respectively

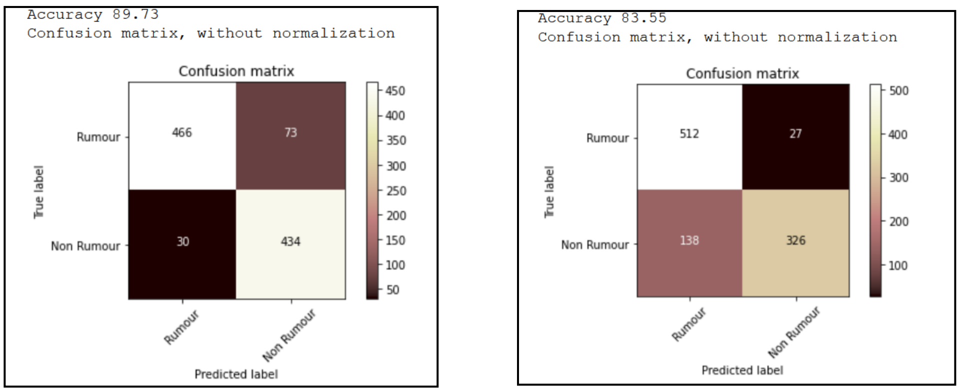

Figure 9: Confusion Matrices for SVM: with Count vectorizer and TF-IDF vectorizer respectively

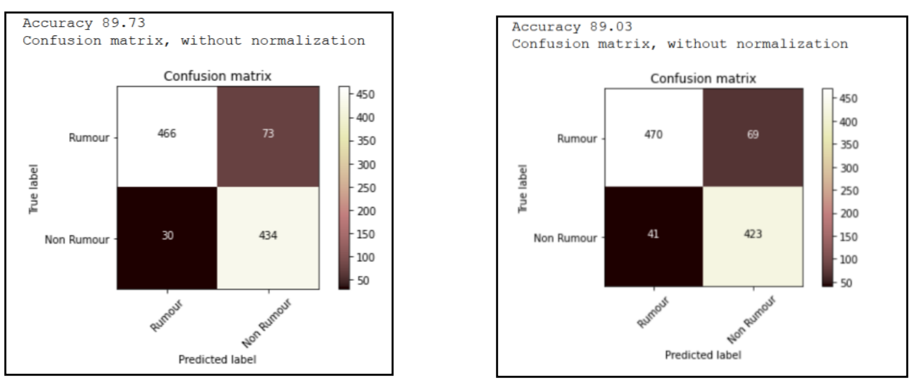

Figure 10: Confusion Matrices for PAC: with count vectorizer and TF-IDF vectorizer respectively

The graph-based comparison of the deep learning implementation (BiLSTM) with prior works of researchers, namely with Hybrid CNN and RNN, Recursive Neural Network, Single (Attention-based) LSTM and CNN-BiLSTM was represented as in Figure 9.

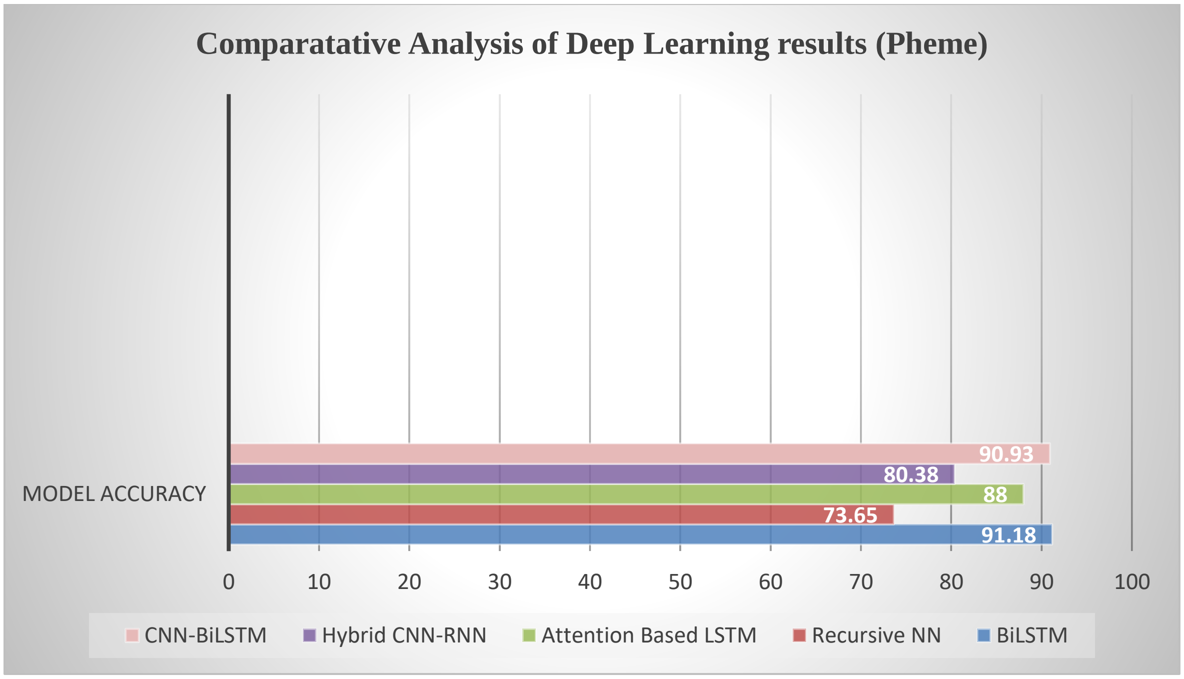

Figure 11: DL performance comparison of models

The performance inferences from the ML based implementation are tabulated below:

Table 2: Performance table (Machine Learning)

Machine Learning Classifier	Count vectorizer Accuracy	TF-IDF vectorizer Accuracy
Random Forest (RF)	88.04%	83.35%
K-Nearest Neighbour (KNN)	80.46%	78.17%
Support Vector Machine (SVM)	89.73%	83.55%
Passive Aggressive Classifier (PAC)	89.73%	89.03%

We observed that PAC classifiers gave the best overall performance accuracy (89.73% using count vectorizer and 89.03% using TF-IDF). It is closely followed by SVM using count vectorizer (Accuracy using count vectorizer being equal), but the performance of SVM using TF-IDF is lower than that of PAC (83.55%) for the same. KNN using TF-IDF proved to be the weakest (78.17%). Overall, too, classifiers utilizing count vectorizer performed better compared to the ones using TF-IDF vectorizers. Results are on the basis of fake news dataset. PAC, due to its inability to converge and update itself in order to rectify loss, performs best. It is observed that TF-IDF generally performs better than count vectorizer. But in our research, the latter provided better results. This could be due to the fact that since it is a binary classification situation pertaining to "rumour" and "non-rumour", count vectorizer was able to give certain words more priority, based on frequency.

Table 3. Performance table (Deep Learning)

Deep Learning Classifier	Accuracy
BiLSTM (model implemented)	91.18%
Single (Attention-based) LSTM (Singh et al., 2020)	88%
CNN-BiLSTM (Rani et al., 2021)	90.93%
Hybrid CNN and RNN (Ajao et al., 2018)	80.38%
Recursive Neural Network (RvNN) (C P et al., 2019)	78.65%

Compared to the prior works of researchers on Attention-based LSTM, CNN-BiLSTM, Hybrid CNN and RNN and Recursive Neural Network based models, Bidirectional LSTMs provided a higher accuracy of 91.18%. The results are on the basis of the dataset Pheme containing rumours as well as non-rumours.

5. CONCLUSION AND FUTURE SCOPE

It is about time that complete scope of deep-learning techniques, including optimized versions of the recurrent and convolutional neural networks, long short-term memory, as well as their hybrid forms starts being utilized. We have models that incorporate these techniques but they are still not equipped to deal with humongous amounts of data. The accuracy these systems provide is fairly average and has abundant scope of improvement as DL-based research it is still in its nascent phase, looking at the greater picture. This in fact is the reason why switching to deep learning from machine learning is suggested as ML models may appear to give better results, but they easily get overwhelmed when data is huge, inconsistent or in real time. Their learning ability is low and even unsupervised models need quite a lot of assistance. In order to obtain better results, training and testing with more data, better pre-processing and treating of missing data, incorporation of hybrid or multiple algorithms/techniques and fine tuning, adjustment of parameters can be helpful. We know that LSTM and traditional RNN based networks work well with textual and in detection systems. But they do lack in dealing with visualization and large sums of data. This is something that CNN can be better equipped for. Therefore, it is imperative to identify the use case and apply techniques accordingly. Like we saw in this paper, LSTMs performed better as the data was textual, while CNN, even though considered more robust and efficient, could not provide better results even in their hybrid versions. The size, type of data determines which classifier proves to be the best. Using embeddings that are already trained in hybrid versions of the above techniques might improvise results for the future.

In the supervised classification, we saw that count vectorizer performed better. This could be because it prioritizes frequency and certain words more, which in a binary analysis could prove to be beneficial. TF-IDF, on the other hand changes results drastically even due to minor changes. In an exhaustive dataset it might not be an issue, but smaller datasets could get affected, as in this case.

Rumours can be much more harmful than they appear, and can greatly influence opinions, the news and reputations of people, places, organizations, and governments. There is a constant need for revolutionizing the way they are dealt with as miscreants and technology evolve.

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