A Research Report

On

An exemplar study on spiking neurons in the field of Fake News Detection

Submitted to **Indian Institute of Information Technology, Allahabad**

In fulfilment of requirements for the award of the certificate

In

Research Internship

Submitted By

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Under the guidance of

Dr. Vrijendra Singh

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CANDIDATE'S DECLARATION

I hereby declare that the work presented in this report entitled " **An exemplar study on spiking neurons in the field of Fake News Detection**", in fulfilment of the requirement for the award of the certificate in research and submitted to **Indian Institute of Information Technology, Allahabad** is an authentic record of my own work carried out during the period from June- August 2020 under the guidance of Dr. Vrijendra Singh, Head of IT Department, IIIT -A.

PRIYANSHI CHAUHAN

ACKNOWLEDGEMENT

I express my deep gratitude to **Dr. Vrijendra Singh**, Head of Department , IIIT-A , for his valuable guidance and suggestions throughout my internship. I am very thankful to his consistent help and mentorship while writing the research paper as well.

No portion of the work referred to in this report has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Priyanshi Chauhan

ORGANISATION INTRODUCTION

Indian Institute of Information Technology (IIIT), Allahabad was established in 1999 as a centre of excellence in Information Technology. The Institute is located at Devghat Jhalwa in Allahabad. IIIT-A has acquired international academic acclaim and recognition.

It is placed in the top 100 technological institutions in the NIRF 2018 ranking list. It provides UG, PG and doctoral level programs.

The Indian Institute of Information Technology Allahabad (IIIT-A) was established in 1999. The institute was conferred as a "Deemed University" in 2000.Among government engineering colleges in India, IIIT-Allahabad ranked 10th by *India Today* in 2019 and 18 by *Outlook India* in 2019.It was ranked 82 among engineering colleges by the National Institutional Ranking Framework (NIRF) in 2019. In 2014 the IIIT Act was passed, under which IIITA and four other Institutes of Information Technology funded by the Ministry of Human Resource Development were classed as Institutes of National Importance.

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WEEKLY PERFORMANCE

Week 1: Read and understand 5 research papers on the previous related works .

I listed the recent works and publications on the topic “fake news detection”.These are listed below -

[1] Kai Shu , Guoqing Zheng. Leveraging Multi-Source Weak Social Supervision for Early Detection of Fake News .arXiv:2004.01732v1, 3 Apr 2020.
[2] Junaed Younus Khan , Md. Tawkat Islam Khondaker .A Benchmark Study on Machine Learning Methods for Fake News Detection.
[3] Jiawei Zhang1 , Bowen Dong2 , Philip S. Yu2 . FAKEDETECTOR: Effective Fake News Detection with Deep Diffusive Neural Network ,[10 AUGUST 2019].
[4] Kai Shu, Amy Sliva, Suhang Wang, Jiliang Tang, and Huan Liu. Fake news detection on social media: A data mining perspective. ACM SIGKDD Explorations Newsletter, 19(1):22–36, 2017.
[5] Yaqing Wang, Fenglong Ma, Zhiwei Jin, Ye Yuan, Guangxu Xun, Kishlay Jha, Lu Su, and Jing Gao. Eann: Event adversarial neural networks for multi-modal fake news detection. In CIKM, 2018

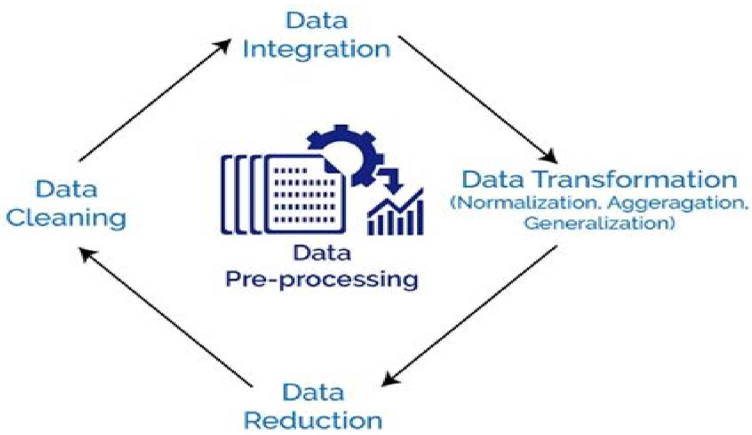
Week 2: Search for the benchmark datasets.

Different datasets have been used for this study in the recent works .In order to search for the benchmark as well as easily accessible dataset

[6] Archita Pathak , K. Srihari . BREAKING! Presenting Fake News Corpus For Automated Fact Checking. Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics.
[7] Kai Shu1 , Deepak Mahudeswaran . FakeNewsNet: A Data Repository with News Content, Social Context and Spatiotemporal Information for Studying Fake News on Social Media.
[8] Tariq Alhindi, Savvas Petridis .Where is Your Evidence: Improving Fact-checking by Justification Modeling , [Proceedings of the First Workshop on Fact Extraction and VERification (FEVER)].

Week 3: Grasp understanding of the workflow and finalise the datasets to be used.

I dedicated this week to the workflow of the project and finally proceed with the three datasets specifically - Fake news corpus , Liar-Plus and Fake news net.



Week 4 : Data preprocessing of one dataset and applied Natural Language Processing .

Exploratory Data analysis , data visualisation, feature extraction , entire NLP process (from tokenization , stemming , stopwords removal,) and vectorization process (using GloVe embeddings) are applied before feeding to the model. Data augmentation is performed for imbalanced dataset.Topic Modelling was done for better understanding of the dataset.

Week 5 : This week is dedicated to the understanding of the deep learning model (S4NN).

Read a few blogs and publications on spiking neural networks to get a better understanding of the same.Decided what to be done as modifications. Also focussed on the maths behind the already proposed equations and logic.

Week 6 : Training of our proposed model and testing the accuracies on other models as well.

During this week , I did modifications in the S4NN model for improving its execution time and made the network deep for better learning of the features by the model.

Week 7 : Repeating the whole process of data analysis and prediction on the remaining two datasets.

WEEK 8 : Completion of the project and writing research paper

In this week, I completed my project and wrote my research paper for the final submission

OVERVIEW OF PROJECT

During the last few years, with advancement in the technologies and with unlimited access to the social networking sites, information dissemination is at its peak. Social media is a prominent source of daily news containing both real ones as well as fake ones. The domain of fake news detection has attained huge attention since a decade and many researchers have dedicated their time and efforts still there is a need of lot improvements in the results. This is because of the limited annotated dataset to work upon as well as the need of more exploration in this domain.

Our research widens the area of exploration to the third generation of deep neural nets and has shown some promising results.The inspiration of introducing spiking neural nets to detect fake news comes from the fact that they have the advantage of being intrinsically sensitive to the temporal characteristics of information transmission .It has been shown that the precise timing of every spike is highly reliable for several areas of the brain and suggesting an important role in neural coding. This precise temporal pattern in spiking activity is considered as a crucial coding strategy. SNNs have become the focus of a number of recent applications in many areas of pattern recognition such as visual processing, speech recognition and medical diagnosis.

Also the model is more hardware friendly and least computationally expensive, requiring few epochs only. Compared to other single spike neural model, the network is made deep by adding one more hidden layer with 1/4th the neurons in other works.

Detection of fake labels is first performed by considering binary classification only and then extended to six-labels classified Liar-plus dataset which has shown encouraging results.

INTRODUCTION

Fake news is targeted propaganda, created intentionally to mislead readers and spreads false information to the targeted audience. Fake news spreads faster and their rapid shares on social networks is alarming. It has now become a global concern because of the fact that it negatively influences economic, political and social well being.

For the time of 2016 US election, several kinds of fake news about the candidates outstretched on the online social networks, which had a significant impact on the election results. As claimed by the post-election statistical report [1], online social media account for more than 41.8% of the fake news data traffic in the election, which is much greater than that of traditional print medium and online search engines.

For example, within the final three months of the 2016 U.S. presidential election, the fake news generated to favor either of the two nominees was believed by many people and was shared by more than 37 million times on Facebook. Therefore, it is in great need of an automatic detector to mitigate the serious negative effects caused by the fake news.

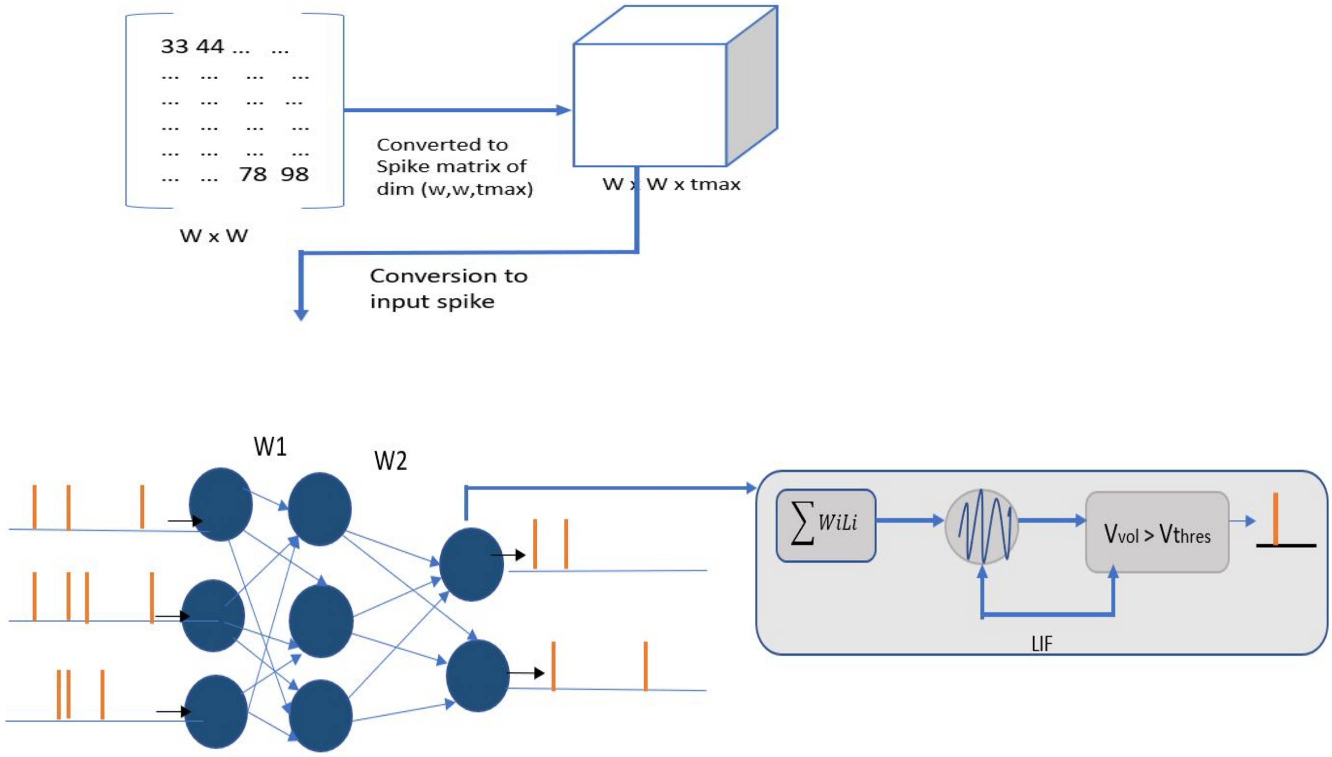
The purpose of the work is to come up with a solution that can be utilized by users to detect and filter out news containing false and misleading information. We use simple and carefully selected features of the title and content to accurately identify fake posts. The experimental results show a 69.9% accuracy using modified S4NN.

The research presented in this paper focuses on a novel learning rule, based on the single spike algorithm, which provides a statistical approach with the advantage of being less computationally expensive than the standard STDP rule, and is therefore suitable for its implementation on stand-alone computational units. The purpose of the proposed model is to learn through more non-linearities through more hidden layers . Also since 4 layers of 100 neurons each is equivalent to 1 layer of 400 neurons ,though we have just used 2 layers of 100 neurons each to achieve good accuracy and more non-linearity.

LITERATURE SURVEY

From the beginning of the decade or so, due to the increasingly realized impacts of fake news , the research community started to devote their time and efforts to the problem for detection of fake news.
To predict the veracity of the online news, Jiawei Zhang , Bowen Dong [2] introduced an automatic fake news credibility inference model, named FAKEDETECTOR to identify the fake news articles, creators and subjects simultaneously from the network with a deep diffusive network model.
Shu, Silva, Wang, Jiliang and Liu [4] used linguistic-based features such as total words, frequencies of phrases (n-grams and bag-of-words pipeline), characters per word, parts of-speech (POS) tagging, frequencies of large words.
Wang in his [5] has built a hybrid convolutional neural network model that outperformed other traditional machine learning models.
Hannah Rashkin et al. [6] have performed an extensive analysis of linguistic features and shown the impressive result of LSTM.
Textual features are statistical or semantic features extracted from text content of posts, which have been explored in many literatures of fake news detection. Ma et al. [7] propose a deep learning model to identify fake news.
However, some work is also done in context of the Generative and discriminative models like GROVER [21]. The best defence against the generative part of the Grover turns out to be Discriminator of Grover itself. The goal of the paper was to understand and respond to neural fake news before it manifests at scale. The framework casts fake news generation and detection as an adversarial game with two players 1. Adversary and 2. Verifier.

ARCHITECTURE OF THE MODEL



Structure of the model -

Table 1: Structure of the model used for different datasets.

	Layer Size				*Initial Weights*			*Model Parameters*			
Dataset	*Input*	*Hidden1*	*Hidden 2*	*Output*	*Hidden*	*Hidden2*	*Output*	*tmax*	η	γ	λ
FakeNewsCorpus	24x24	100	100	2	[0 ; 5]	[0 ; 5]	[0 ; 48]	256	0.2	3	10^{-6}
Liar plus	8x8	100	100	6	[0 ; 5]	[0 ; 5]	[0 ; 48]	256	0.2	3	10^{-6}
FakeNewsNet	4x4	100	100	2	[0 ; 5]	[0 ; 5]	[0 ; 48]	256	0.2	3	10^{-6}

FUTURE WORK

Future work involves training on the large datasets as we have trained our model on the sampled (minimalistic) data only.
Our simple method for detection is somewhat less accurate on FakeNewsNet dataset.We plan to further increase the accuracy with more careful feature selection.
Single-Spike-Supervised-network has the potential to facilitate many promising research directions such as fake news mitigation, malicious account detection , deceptive sites detection ,etc
There are several interesting options for future work.
First,training on very large datasets(such as credbank,pheme etc) can be done by making the network deep so as to extract relevant features.
Second, training on larger dataset will involve difficult hardware implementation, thus focussing on the practicality of the hardware to be used.

RESULT & CONCLUSION

I outline the empirical results in Table 2. First, I have compared various models using text features. I observed that the majority baseline on FakeNewsCorpus gives about 0.68 accuracy with the modified S4NN having 0.69 accuracy. Standard text classifiers such as Naive Bayes obtained significant improvements. Due to overfitting, the Stacked-LSTM did not perform well. The modified S4NN outperformed all models, resulting in a consistent accuracy of nearly 70% on each dataset . The maximum accuracy of modified S4NN (MS4NN) has a consistent test performance of nearly 0.70, unlike other models which have fluctuating accuracies on the datasets (showing lots of ups and downs on different datasets).

Table 2 : Results shown on different datasets by different models.

	FAKE NEWS CORPUS	**LIAR PLUS**	**FAKENEWSNET**	
			POLITIFACT	**GOSSIPCOP**
MODELS	2 classes	Multi-class	2 classes	2 classes
S4NN	**73.26 %**	62.70 %	40.70 %	58.77%
MODIFIED S4NN	**69.39%**	**69.9 %**	40.75 %	64.32 %
STACKED LSTM	35.45 %	21.37 %	20.87 %	20.87 %
ATTENTION LAYER	68.73 %	**83.33 %**	70.00 %	-----
NAIVE BAYES	68.62 %	20.68 %	66.91 %	48.89 %

I have successfully trained the model on sufficient data and I take this opportunity to express my sense of indebtedness and gratitude to all those people who helped me in completing this project.

I am immensely grateful to my esteemed mentor **Dr. Vrijendra Singh** for his guidance without which this work would not have been possible. This project has contributed a lot to my knowledge that has proved to be a value addition for me.

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