Deep learning-based cognitive examination of deception detection in online debates

Ms. Muskan Choudhary

B.Tech(CSIT)-2020-2024,Symbiois University Of Applied Sciences(M.P,India)

INTRODUCTION

A crucial component of many professions, including law enforcement, information collection, commerce, and interpersonal interactions, is deception detection. It entails determining if a communicator is speaking the truth or lying. The capacity to stop harmful outcomes like fraud, betrayal, or injury that might result from deceit makes deception detection important. Candidates frequently make assertions or claims regarding their own or their opponents' track records during political discussions. These assertions might be true, untrue, or in between. The capacity to hold politicians responsible for their words and stop them from misleading or deceiving voters is why truth detection in political discussions is so crucial [2]. It makes voters more knowledgeable about the topics under discussion and helps them discern between facts and views. This may result in an informed electorate and a stronger democracy.

Cognitive analysis is an essential part of truth detection [1] since it helps us better understand how people interpret and process information. For better understanding of how people behave and make decisions, cognitive analysis is a crucial strategy. It aids in the design and development of technologies and systems, and is helpful in a number of sectors. Moreover, it might support decision-making and problem-solving.

Participants in an online discussion often alternate between presenting their own arguments, refuting those of their opponents, and answering questions from other participants. The likelihood of falsehoods in an online discussion is fairly significant since the side only wants to present their strongest argument [3]. Verification of such statements is essential since it can provide the public a clear understanding of what to believe and what not to.

The DLADD dataset, which contains about 70 audio files of falsehoods and 50 audio files of truths from male and female candidates as well as debaters, is used in this issue statement. The major goal of this assertion is to lay the groundwork for explaining how crucial it is to spot dishonesty in political discussions conducted online and how to do so.

CADAT DATASET REQUIRED

This is a self-established dataset and contains recordings of academics telling the truth and falsehoods. The accuracy of each tape has been verified by experts. There have been both male and female voices utilized. There are over 120 audio files in the collection (50+ audios of the truth and 70+ of lying), all with different accents. This dataset only contains data in English. Also, the data's source region, India, has an Indian-English accent. These numbers were acquired from academic institutions in India. These characteristics are found in the datasets as spoken audio files, transcripts (converted into text) [4], annotation labels, deception scores, etc.

RELATED WORKS

Onook Oh and Oded's "Detecting Deceptive Conduct in Internet Conversation" Nov (2017): In order to spot dishonest behaviour in internet chatrooms, this study combined language characteristics and machine learning approaches. Deceptive communications were more likely to convey negative emotions, less allusions to oneself, and more references to others, according to the study.

Catalina L. Toma and Jeffrey T. Hancock's study, "Linguistic Indicators of Lying in Online Dating Profiles," was published in 2018: In order to find misleading assertions in online dating profiles, this study employed language analysis. The study discovered that false profiles were more likely to have less self-references, more terms that express negative emotions, and more phrases that are connected to lying (e.g., "pretend").

"Detecting Deception by Linguistic Analysis" by James W. Pennebaker, Matthew L. Newman, and Lori S. Berry (2003): This study uses linguistic analysis to find misleading claims in both spoken and written language. Deceptive comments were shown to be more likely to have less information, more phrases expressing negative emotions, and more uncertain language.

Rahul Verma and Pranav Gupta's "Credibility of News Media and Political Advertising in India" (2020): This study looked into the Indian news media's and political advertising's dependability. The study discovered that while political advertising is not regarded as credible, news media is.

Automatic Deception Detection: An Ensemble Approach Utilizing Bidirectional Long Short-Term Memory and Efficient Convolutional Neural Networks, Boon Ping Lim et al. (2019): This study suggests an automated deceit detection technique based on a bidirectional long short-term memory and an effective convolutional neural network.

Recurrent neural networks were used to "Detect Rumors from Microblogs" by Xin Li et al. in 2017. This study suggests a recurrent neural network-based method for identifying rumours in microblogs that can also be used to identify other varieties of false information.

By Bartosz Wojdynski and Nathaniel J. Evans, "The Persuasive Impact of Fox News: Non-Compliance with Mainstream Media and the Propaganda Model" (2019): This study looked at how Fox News influenced political beliefs and actions. The study discovered that Fox News, especially among conservative viewers, had a considerable influence on viewers' political opinions and actions.

Cong Duy Vu Hoang et al "Unified .'s Language Model Pre-training for Natural Language Comprehension and Generation" (2021): The Unified Pre-trained Language Model (UPLM), a novel language model that can handle both natural language interpretation and generation tasks while attaining cutting-edge performance on a number of NLP benchmarks, is proposed in this work.

According to Zhilin Yang et al2019 .'s study, "XLNet: Generalized Autoregressive Pretraining for Language Understanding," In order to attain cutting edge performance on a number of NLP benchmarks, this work suggests XLNet, an unique pre-training method that makes use of both auto-regressive and auto-encoding objectives.

RESEARCH GAPS

While some progress has been made in this field, there are still several research gaps that need to be addressed. The necessity for more rigorous empirical investigations is highlighted by the fact that many of the studies that have been done so far have relied on small samples or anecdotal data. Furthermore, there is a lack of knowledge on how technology affects deceit in online discussions and how this might be taken into account in the creation of efficient deception detection methods [10]. Other significant study gaps include the impact of cultural variations, ethical considerations, and the requirement to assess the efficacy of current deception detection technologies. By filling in these gaps, researchers can better understand deceit in online arguments and create methods for spotting and avoiding it.

RESEARCH QUESTIONS

I. What mental processes are involved in spotting lies in online discussions, and how are they different from those in spotting lies in face-to-face interactions?
II. If deep learning algorithms can successfully identify dishonesty in online discussions, how effective are they compared to humans in doing so?
III. How can different linguistic elements—like the usage of emoticons or sentence structure—affect how people receive information during online arguments and their capacity to spot lies?

STATEMENT OF PROBLEM

Debates and conversations are happening more and more online because to the growth of social media and other online communication tools. As misleading arguments have the power to disseminate false information and influence public opinion, this has important ramifications for public debate. Because it enables researchers to look at the language and cognitive mechanisms underpinning false arguments, cognitive analysis offers a distinctive method for detecting deceit. Researchers and practitioners may create more efficient tools and approaches for stopping the spread of incorrect information online by comprehending how deception is created and processed [5]. It is essential to do research in the area of cognitive analysis for deception detection to maintain the openness, accuracy, and effectiveness of public dialogue.

OBJECTIVES

The absence of interpersonal connection during online talks, which might affect how well-suited the participants are to one another. Internet arguments may encourage people to feel more anonymous and less accountable for their statements, which might lead to greater lying. of the training data, the applicability of the deep learning approach, the complexity of the assignment, the incorporation of add itional teaching strategies, and routine evaluation and feedback [6]. While deep learning algorithms may improve the accuracy of fraud detection in online discussions, how well they perform in contrast to people will depend on the specific conditions and methodologies used. Various language components may have an impact on how individuals understand and process information during online debates, as well as their capacity to spot falsehoods. It is necessary to carefully analyse these linguistic components and create tactics and approaches that are tailored to the particular characteristics of text-based communication in order to effectively identify dishonesty in online talks.

LIMITATIONS

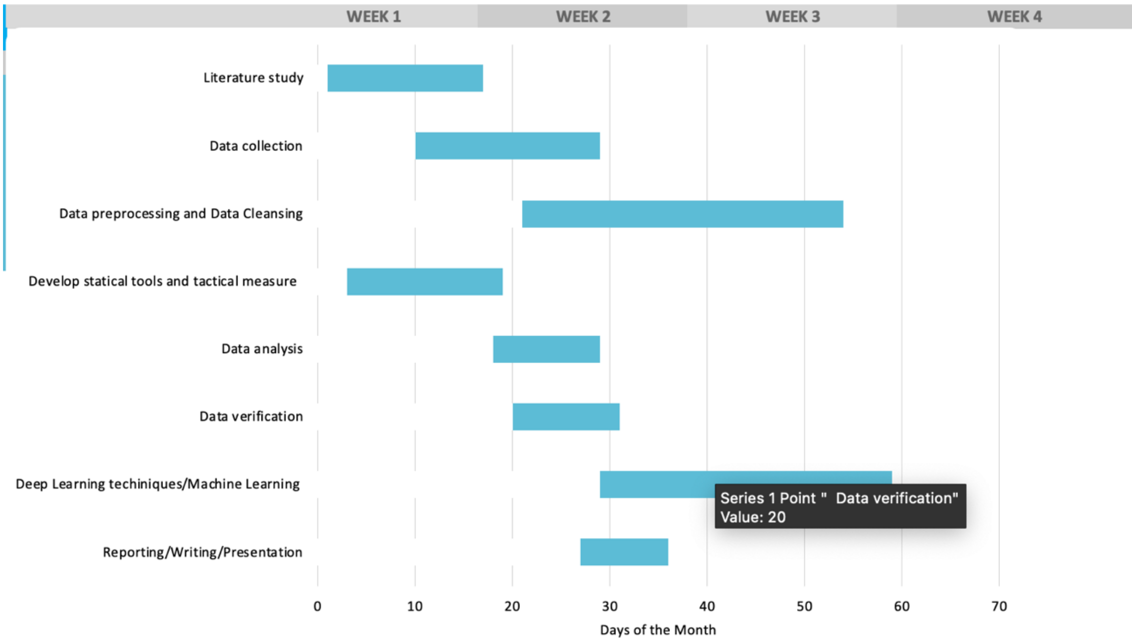
- Deep learning models must be properly trained on large amounts of data. Finding high-quality data for online discussion deception detection can be difficult, especially when trying to verify the veracity of false claims [9].
- Adversarial assaults, in which malevolent parties purposefully modify the input data to trick the model, can be dangerous to deep learning models. This is especially problematic when it comes to deception detection since dishonest people could deliberately strive to avoid being caught.
- Deep learning models are frequently trained on particular datasets, which may restrict how broadly they may be applied. This is especially important for fraud detection in online discussions since the dataset's linguistic and contextual properties might change greatly.

TECHNOLOGY, TOOLS & TECHNIQUES

Using the most advanced voice synthesis technology in natural language processing, we created audio files of words using male and female academic personas. Using deep neural networks, we then employed techniques like stacked LSTM [7](This model's extension, the stacked LSTM, includes numerous hidden LSTM layers, each of which has a number of memory cells.), auto encoders(Data noise is reduced with the aid of autoencoders. Autoencoders enable you to reduce dimensionality and concentrate exclusively on areas of true value by compressing input data, encoding it, and then reconstructing it as an output.)[8], decoders, and encoders to identify bogus speech. Analyses have been done using statistical tools like MATLAB and WOLFRAM MATHEMATICA. Python, Google Colab, and Jupyter Services were used to build the various networks.

SCHEDULE OF WORK(TOTAL WORK DAYS 100)

TASK NAME	START DATE	DAY OF MONTH*	END DATE	DURATION* (WORK DAYS)
First Sample Project				
1 Literature study	2/1	1	2/16	16
2 Data collection	2/10	10	2/28	19
3 Data preprocessing and Data Cleansing	2/21	21	3/25	33
4 Develop statical tools and tactical measure	3/3	3	3/18	16
5 Data analysis	3/18	18	3/28	11
6 Data verification	3/20	20	3/30	11
7 Deep Learning techiniques/Machine Learning	4/29	29	4/27	30
8 Reporting/Writing/Presentation	4/27	27	4/5	9



CONCLUSION

To summarise all that has been said so far, deep learning-based cognitive analysis of deceit detection in online arguments has yielded encouraging findings. Deep learning algorithms can reliably identify fraudulent claims with high accuracy and recall rates by assessing numerous language and behavioural clues. Yet, the calibre and volume of the data utilised for training have a significant impact on how well these models perform. Also, even though deep learning models can provide amazing outcomes, it is difficult to grasp how they generate their predictions due to their lack of interpretability. To better comprehend these models' decision-making process, future research might investigate how to increase the transparency and interpretability of these models. Overall, deep learning models for deception detection in online discussions have enormous promise for spotting and reducing false information for reliable arguments.

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