COGNITIVE ANALYSIS OF TRUTH DETECTION IN ACADEMIC TEACHING USING DEEP LEARNING

Ms. Muskan Choudhary

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

INTRODUCTION

Deception detection is essential since it fosters trust. It aids in preserving a righteous person's dignity and also recognizes and corrects a wrongdoer. It is useful in the academic world since it enables teachers to make sure that they are giving their students accurate information. When instructing, it is crucial to provide knowledge that is backed up by facts and to dispel any myths that the pupils may have heard. Teachers can encourage in their students a sense of trust, critical thinking, curiosity, and lifelong learning. Finding the truth can increase confidence, inspire critical thinking, spark curiosity, and advance learning.

As it enables us to better understand how individuals interpret and analyze information, cognitive analysis is a crucial component of truth detection. It is the process of examining how people reason, think, and act when presented with new information. Cognitive analysis can assist us in understanding why people might have particular beliefs and how they assess the veracity of information in the subject of truth detection[1]. Teachers and students can create ways for analyzing material more properly and objectively by being aware of certain cognitive biases.

Assuring that the knowledge being taught and researched in academia is correct, truthful, and reliable requires the identification of truth and falsehoods in academic instruction[2]. In addition to assisting in the fight against false information and fake news, it encourages critical thinking, intellectual honesty, and the integrity of research. The search of knowledge and the growth of understanding are the foundational principles of academia, and these goals can only be met with precise and genuine information.

In this problem statement, the audio sequence from the CADAT dataset—which includes 50 false and 50 true video clips—was employed. Speech signals are taken from the video clips in this case because the speech signal is used to do the lie detection[3]. The dataset contains a carefully labelled collection of talks by academics and educators, both male and female, who use various accents to tell the truth and lies.

CADAT DATASET REQUIRED

The audio for the words is produced using the most advanced voice synthesis technologies. This is a self-created dataset that includes audio of professors speaking both the truth and lies, with each recording having been reviewed by specialists to determine its veracity. There have been both male and female voices utilised.There are 50 lying audios and 50 truth audios in male and female sector, all with various accents. There are only English-language data in this dataset. Also, the region from which the data is gathered, namely India, has an Indian-English accent. These statistics were gathered from Indian universities and schools. These attributes include voice audio files, transcripts (converted NLP text)[4], annotation labels, deception scores, etc. in the datasets.

RELATED WORKS

Tim van Gelder's "Teaching Critical Thinking: Some Insights from Cognitive Science" (2005). Insights from cognitive science are used in this article to discuss instructional methods for critical thinking. The author stresses the need for students to have opportunity to exercise critical thinking skills in real-world situations as well as the significance of formal training in these skills.

Mohamed Seghier and colleagues' "The Neural Basis of Deception Detection: A Meta-Analysis" (2012). The brain areas that are consistently active during deception detection tests were identified in this study using meta-analysis. The findings demonstrated that deception detection involves the prefrontal cortex, anterior cingulate cortex, and inferior parietal cortex.

Aldert Vrij and colleagues' "Cognitive Processes in Deception Detection: Evidence from Cognitive Load Manipulations" (2000). This study looked into how accurately detecting dishonesty is affected by cognitive load. The findings indicated that cognitive load can reduce the accuracy of deception detection, indicating that it is a mentally taxing endeavour.

Tim Levine and colleagues' "Cognitive Biases in Truth Detection and their Links to Deception" (2016). The accuracy of truth detection was compared to cognitive biases in this study. The findings demonstrated that a number of cognitive biases, including the truth bias and the familiarity bias, might result in mistakes when determining the truth.

Stephan Lewandowsky and colleagues' study, "The Role of Confirmation Bias in Susceptibility to Misinformation" (2012). This study looked into how confirmation bias affects a person's receptivity to false information. The findings demonstrated that even when information is erroneous, people are more inclined to accept it if it confirms their own ideas.

Maria Hartwig and Pär Anders Granhag's "The Cognitive Basis of Lie Detection." In this study, the cognitive mechanisms of deceit detection are examined, along with the role of context and information in deception detection.

By Mohd Fairuz Shiratuddin et al., "Emotion-based technique for deception detection utilising physiological signals." This study explores the use of physiological markers, such as skin conductance and heart rate, to identify dishonesty depending on the subject's emotional state.

RESEARCH GAPS

As of right now, there is no defined procedure for carrying out cognitive analysis of truth detection. Because of this, it may be challenging to compare the findings of different studies and to formulate definitive judgements about the cognitive processes involved (contextual considerations, cross-cultural variances, individual differences, and real-world application). Most studies on the cognitive analysis of truth detection are carried out in controlled environments, which could not adequately reflect actual circumstances. To further understand how truth detection cognitive processes are applied in practical contexts, such as legal and investigative settings, more research is required.

RESEARCH QUESTIONS

I. How successful are deep learning approaches in academic settings for teaching cognitive analysis abilities related to truth detection?

II. What are the main elements that determine whether deep learning-based approaches to teaching truth detection are successful or unsuccessful?

III. How do various speech data types (such as scripted versus unstructured speech) impact the precision of deep learning models for truth detection?

STATEMENT OF PROBLEM

The development of standardized methods for conducting cognitive analysis of truth detection. This would enable more reliable and rigorous comprehension of the related cognitive processes as well as more consistent and comparable outcomes across research. The use of neuroimaging techniques, such as functional magnetic resonance imaging (fMRI)[5], to better understand the neural mechanisms involved in truth-finding and provide a more in-depth understanding of the cognitive processes involved is another potential area for future research. This approach could have significant implications for the creation of interventions to enhance truth-finding abilities. To create automated truth detection systems, machine learning approaches could be used with cognitive analysis of truth detection. This may have significant uses in industries including media, law enforcement, and academia.

OBJECTIVES

The creation of precise learning objectives, the curation of high-quality datasets, the selection of appropriate techniques, the provision of engaging instructional materials, the promotion of student engagement, the monitoring of progress, the provision of feedback and evaluation are all examples of best practises for integrating deep learning techniques into academic teaching for truth detection[6]. By utilising vast amounts of annotated data to train deep neural networks to discern patterns of deception in speech, deep learning techniques have demonstrated promising results in teaching students how to recognise patterns of deception in speech. This strategy can teach students to recognise crucial deception indications, such as variations in pitch, tone, and rhythm, and can offer a more unbiased and data-driven strategy for truth detection. The effectiveness or ineffectiveness of deep learning-based approaches to teaching truth detection depends on a number of important variables, such as the calibre and diversity of the training data, the suitability of the deep learning technique, the difficulty of the task, the integration with other teaching techniques, and regular evaluation and feedback.

LIMITATIONS

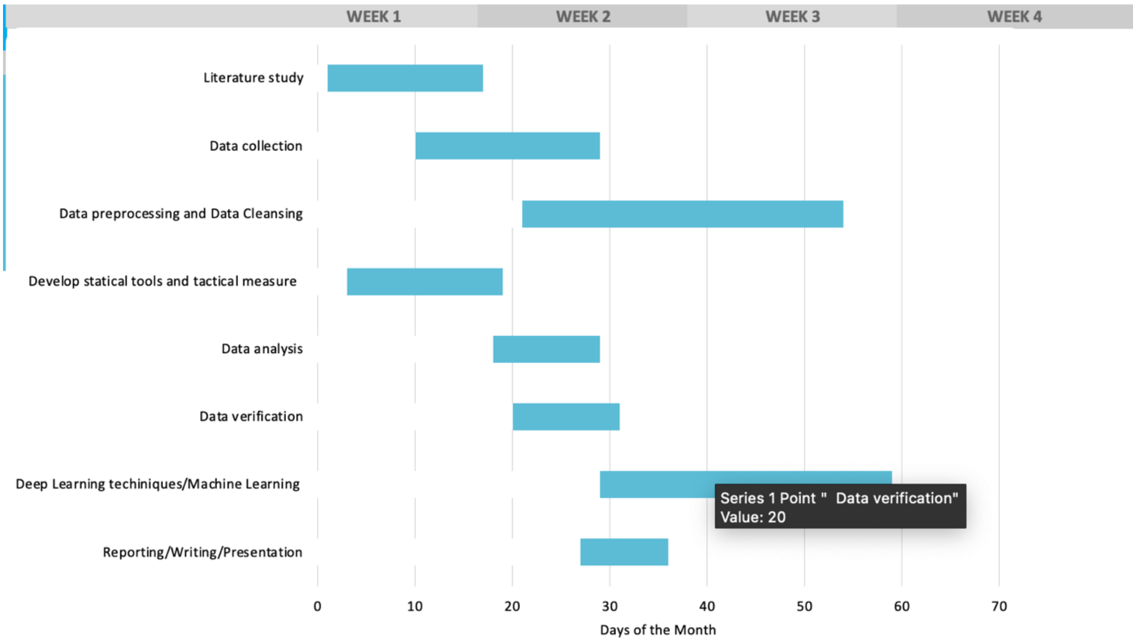
- “ASVspoof” databases, among other potential datasets, have been created to impede the advancement of fake audio detection. [6] Previous datasets, however, omit an attack scenario where a hacker conceals a few minute-long phony recordings in real voice sounds. Due to the difficulty in separating the brief fake clip from the entire speech utterance, this poses a major hazard.
- The notion that there are universal patterns of deceit that can be recognized across different people and cultures is one of the limitations of cognitive analysis in truth detection. This could not always be the situation.
- Another drawback of cognitive analysis in truth detection is that it could overlook contextual elements that can affect a statement's truthfulness, such as cultural variations, unique personality qualities, or the particular setting in which the statement was made[4].

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 DAYS PLAN -100 Days)

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, cognitive analysis is an area of learning and identifying one of the most perplexing patterns. Years of training and many data variations will be necessary for an artificial intelligence to correctly detect the deceit. Even if it's far away, this comment illustrates how significant and vital it may be once it's created. The implementation will be essential to spotting falsehoods in a variety of contexts, including academia, where both instructors and students may benefit from such deception detection.

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