LieVis: A Visual Interactive Dashboard for Lie Detection Using Machine Learning and Deep Learning Techniques

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Abstract. Lying poses a significant concern in our everyday lives, impacting social interactions. The human face represents a crucial avenue for lie detection, providing a valuable source of data that offers reliable indicators of liars. The skill of detecting lies or deceitful statements is of immense value, mainly due to the elusive nature of the underlying patterns associated with lying. Numerous studies have extensively explored lie detection, employing various advanced techniques. Researchers have devoted their attention to devising more effective and efficient solutions for lie detection. However, there remain ongoing challenges, particularly in achieving higher accuracy levels. Although, there has been relatively limited focus on developing visually interpretable and interactive systems for lie detection. Therefore, we leveraged artificial intelligence, incorporating machine learning and deep learning techniques, to augment the existing system and develop a comprehensive lie detection model. We introduced a dedicated interactive visualization dashboard called LieVis, meticulously designed to facilitate comprehensive exploration of the obtained results. The evaluation of LieVis showcases its superiority over existing methods. Additionally, LieVis offers explanatory insights into the responsible utilization of the underlying AI approach, showcasing its potential to enhance lie detection and intervention strategies. The Python source code for our proposed dashboard with result visualization is available on our GitHub repository [1] and the live dashboard of our dshboard is available here: .

Keywords: Lie Detection· Deep Learning · Machine Learning · Visual Dashboard.

1 Introduction

Lying or deception involves the deliberate act of convincing others to accept false information as true, employing facial expressions and body gestures [8].

[1] https://github.com/

This prevalent phenomenon has contributed to the rising crime rates worldwide. Referring to the Crime Statistics Malaysia 2020 report, there was a notable 24.7% increase in the number of corruption cases. The majority of these cases investigated by the Malaysian Anti-Corruption Agency in 2019 involved bribery (79.0%) and fraudulent claims (35.8%). Lying encompasses a wide range of behaviors and can be influenced by various factors such as individual differences, cultural norms, and situational context. Moreover, in business, lying or dishonesty during the hiring process result in poor recruits that could affect the company's reputation and efficiency as well as cause financial losses [10]. As lying becomes increasingly prevalent, it poses a significant social challenge with wide-ranging consequences in various sectors. The ability to detect lies is crucial, as it not only helps in uncovering dishonesty but also facilitates the development of stronger interpersonal relationships by providing insights into others' motivations and intentions.

In the long history of mankind, it has been a significant social challenge to detect liars [7]. Researchers have been persistently exploring conventional approaches to leverage lying indicators in order to develop a comprehensive lie detection model. For example, Pérez-Rosas et al. introduced a multi-mode lie detection methodology that utilized a unique dataset obtained from actual public court trials [13]. The approach involved combining diverse modalities such as linguistic cues, gestures, and facial features to classify deceptive behavior. Borza et al. [5] conducted a study that presents the utilization of the direction of gaze, eye movements, and blink rate to differentiate between truthful and deceptive behaviors. While previous studies have facilitated the analysis of lying characteristics, they still possess certain limitations. Additionally, the facial images captured are often taken in diverse settings and poses, which can potentially impede model learning. A major hindrance in lie detection research is the scarcity of available datasets, despite numerous studies being conducted in this field. Obtaining reliable ground truth data, which involves accurately determining whether a person is being truthful or lying, poses a primary challenge. Despite these difficulties, the development of a comprehensive and foolproof lie detection system that can accurately detect lying in all circumstances remains a challenging task.

The progress of Artificial intelligence (AI) brings improvements to every aspect, including the field of lie detection. Various AI-based techniques have been employed to categorize lying factors. Machine learning (ML) and deep learning (DL) are forms of AI that can help to identify patterns and make predictions based on data. While previous studies have utilized the advancements of DL and ML, certain factors still require further improvement. Although, visual interactive system (Vis) is still unexplored in this whereas it's frequently utilized for various tasks, including sentiment analysis, mental health analysis, disease diagnosis, suicidal ideation detection, and recommendation systems. While previous studies have predominantly concentrated on classification algorithms for lie detection, there is a need to place greater emphasis on effectively visualizing and interacting with the data. This approach enables users to comprehend the results and make informed decisions. To address this limitation, we introduce an interactive visualization dashboard, which provides users with an intuitive and accessible means to analyze the performance of ML and DL models. In addition to focusing on ML and DL classification algorithms for identifying deceptive behaviors, we also emphasize the interactive visualization of the results obtained from these methods. Consequently, this study delves into the exploration of an interactive visualization dashboard that leverages the outcomes to identify lying behaviors.

The main goal of this research is to analyze the contribution of different features and identify the most significant one associated with individuals who engage in lying. Additionally, several ML and DL methods are applied based on the text and annotation data, and the performances of these models are visualized. In order to achieve the desired outcome, a range of techniques including BERT, LSTM, BiLSTM, RF, SVM, GaussianNB, LR, and K-Neighbors are employed. The models are employed to obtain results, and based on their performance, an interactive dashboard is developed to facilitate the exploration and visualization of the performance of each model. This dashboard would enable users to explore the results and gain insights into lie detection in a user-friendly and interactive manner. Thus, this study makes three significant contributions, as outlined below.

- First, we provide a comprehensive analysis of existing lie detection techniques, both verbal and non-verbal features, and their significant role in the process. Additionally, we identified the distribution of facial expressions in relation to truthful and lying behavior.
- Second, we employed a range of ML and DL methods to categorize the characteristics of lying and truthful data, aiming to determine the model's ability to detect lying behaviors with utmost accuracy.
- Lastly, we have developed an interactive dashboard named *LieVis* that allows users to explore the obtained results and visualize the performance and accuracy of each model in a clear and interactive way.

The following sections provide an overview of the organization of the remaining paper: Section 2 presents the related work that has been discussed. Section 3 covers various aspects such as data collection, processing, contribution of features, distribution of non-verbal features, and methodological analysis. The analysis of the experiment and its results are described in Section 4 and Section 5, respectively. Finally, Section 6 concludes the paper and outlines future objectives.

2 Related Work

In the past, lie detection attempts relied on physiological sensors, but these approaches had significant drawbacks. One notable drawback was the potential bias in human judgment, leading to low classification accuracy in different cases. Moreover, these methods demanded substantial time and effort for analysis. However, with the advent of AI and ubiquitous computing, new opportunities have emerged across multiple domains, including the field of lie detection. Researchers have begun exploring the application of these technologies in the domain of lie detection. A majority of the studies have centered around DL and ML models, which are employed for the classification or prediction of lying behaviors. For example, Srivastava et al. developed a model to identify lying by utilizing speech and physical features of 50 subjects. The training and testing of the model were conducted using Support Vector Machines (SVM) and Artificial Neural Networks (ANN) [17]. Rajoub et al. introduced the concept of thermal imaging for assessing the stress levels of individuals based on the heat radiation emitted from their faces. By analyzing the thermal variations in the periorbital regions, they successfully distinguished between truth-tellers and liars [15].

Table 1. Key Studies on Various Methods for Lie Detection

References	Key purposes	Model
Barsever et al. [4]	Identified patterns and showed the differences between deceptive and truthful text	BERT
Ceballos et al. [6]	Identified the textual cues used in detecting lies across various forms of text-based communication	SVM, NB, RF, LR, DT
Ahmed et al. [2]	Proposed chunking, equal ratio, and DL to increase the effectiveness of lie detection system	LSTM
Ott et al. [11]	Developed the first large-scale dataset containing gold-standard deceptive opinion spam	SVM, NB
Yang et al. [20]	Proposed a novel feature ETF for lie detection in videos	SVM, DT, KNN
Qureshi et al. [14]	Proposed a versatile model that can capture lying	RF, SVM, DT, and KNN

Moreover, Perelman et al. employed eyeblink rate as a means to detect lies [12]. During the research, they collected eye blink frequency data using electromyography and video recordings. The findings revealed that liars exhibit controlled eyeblink rates during lying, whereas truth-tellers demonstrate higher eyeblink frequencies during questioning. A discriminant function was utilized, achieving an 88.2% sensitivity and 73.3% specificity in correctly identifying lying. This method presents a potential alternative to polygraph testing and is compatible with distance technology, offering opportunities for future experiments. Thannoon et al. developed and implemented a lie detection system called "Deception Detection System (DDS)" [18]. The method aims to differentiate between lying subjects and innocent individuals by analyzing the presence or absence of specific facial Action Units (AUs). Eight AUs were utilized as markers for lie detection and were integrated into a unified facial behavior pattern vector. The system achieved accuracy rates of 84%, 85%, and 90% when identifying liars while being effective for both male and female subjects.

Feng et al. introduced an enhanced computer vision-based approach for detecting lies in video streams, building upon previous research. The proposed method focuses on detecting a series of facial expressions in real-time on a target human face. The extracted expression vector is then utilized to classify the video as either a lie or a truth statement [9]. Venkatesh et al. conducted a study exploring a visual-only approach for lie detection [19]. They extracted visual features using a Convolutional Neural Network (CNN) from video input and fed them into an LSTM sequence learning model for binary classification. The results obtained demonstrated the exceptional performance of their developed method, surpassing that of four different state-of-the-art techniques. This research highlights the effectiveness of leveraging visual features and sequence learning models for accurate lie detection.

In conclusion, the existing research has predominantly emphasized the utilization of diverse AI techniques while considering various factors for lie detection. However, there is a lack of studies that have integrated both ML and DL techniques with the visual component. In order to address this, our study aims to explore the task of lie detection by combining Vis with a diverse range of ML and DL techniques. By leveraging this interdisciplinary approach, we seek to enhance the accuracy and effectiveness of lie detection methods.

3 Methodology

In this section, we describe how ML and DL techniques are employed in a dashboard for exploration, design, and implementation as shown in Fig. 2. Moreover, this section provides comprehensive details on data collection and processing, the contribution of features, and the distribution of non-verbal features among truth-tellers and liars.

3.1 Data Collection

During our experiments, we use a multimodal lying dataset obtained from real-life court trials. In order to provide a comprehensive overview, this section includes a detailed description of the dataset [13].

Dataset Overview: The dataset comprises recordings of trial hearings procured from publicly available sources. The videos were carefully chosen to represent a single subject with his or her face visible for the majority of the clip's runtime and to be of a reasonably good audio-visual quality. To assemble the dataset, three distinct trial outcomes were considered to accurately classify trial video clips as either deceptive or truthful. These outcomes included guilty verdict, non-guilty verdict, and exoneration. The final dataset encompasses a total of 121 videos, consisting of 61 deceptive trial clips and 60 truthful trial clips. The videos in the dataset have an average duration of 28.0 seconds, with deceptive clips having an average length of 27.7 seconds, and truthful clips averaging 28.3

seconds. The dataset comprises recordings from 21 unique female speakers and 35 unique male speakers, with their ages approximately ranging between 16 and 60 years.

Transcriptions: Transcriptions were collected from the video dataset. The final set of transcriptions comprises 8,055 words, with an average of 66 words per transcript. Table 2 presents a selection of sample transcriptions illustrating both lying and truthful statements.

Annotation: A meticulous annotation dataset was created, focusing particularly on the annotation of facial displays and hand movements associated with truthful and deceptive behavior.

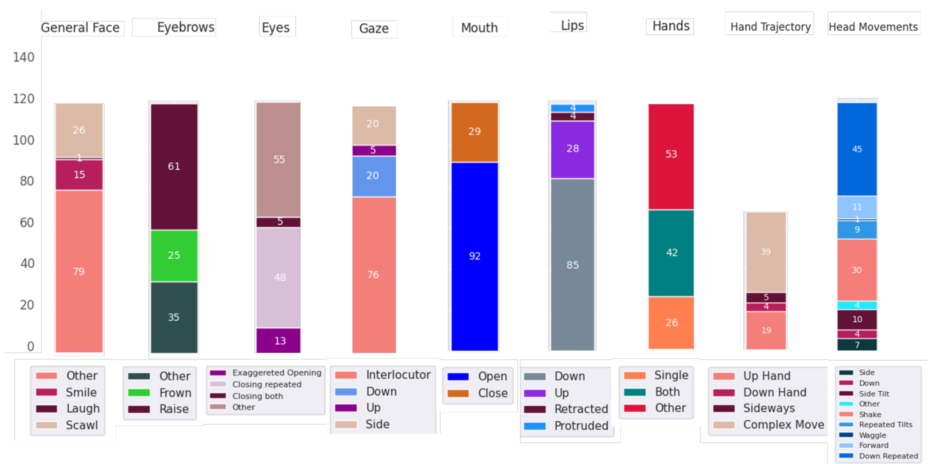

Fig. 1. Distribution of non-verbal features for deceptive and truthful groups

Table 2. Sample transcripts for deceptive and truthful clips in the dataset

Truthful	Deceptive
But yes, I was there. Yep, I stayed. Uh ... Yep, prob – yes, yes.	No sir I was not, not at all.
And I am gonna go forward with this ... because I know I had nothing to do with this crime.	Why would she take a hammer and hit him...
Ahhh ... a lot of people don't value the freedom until it's gone and then when you get it back, it's like you value it a lot more.	No sir I did not. I absolutely did not. No sir I was not. No sir.

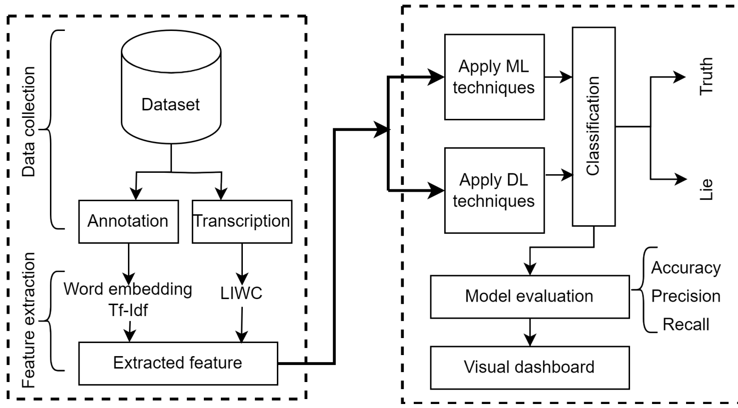

Fig. 2. Architecture of LieVis

3.2 Feature Extraction

The feature extraction process involves capturing both verbal and non-verbal features, encompassing a wide range of aspects [1]. This encompasses extracting and analyzing various cues such as speech, linguistic content, tone of voice, facial expressions, hand gestures, body movements, and other non-verbal indicators that can contribute to identifying deceptive behavior [21]. In this section, we provide a description of the extracted features from each modality. These extracted features will subsequently serve as inputs for constructing lying classifiers.

Verbal Features: Verbal features are derived from the transcripts of video clips. These features capture valuable information from spoken words, enabling the detection of deceptive behavior. For analyzing verbal features, the LIWC (Linguistic Inquiry and Word Count) tool is utilized [3]. LIWC helps gain insights into the semantic categories of words used in the transcripts, providing meaningful clues for lie detection. By applying LIWC, we identify specific linguistic patterns and expressions that might indicate lying tendencies. After extracting features through LIWC, various ML models are employed to process and analyze the data. By comparing the performance of different models, we can identify which ones exhibit the best accuracy and effectiveness for lie detection based on verbal features.

Non-Verbal Features: The non-verbal features are obtained from the annotation process. Each feature signifies the presence of a gesture only if it is consistently observed during the majority of the interaction. These features encompass nine distinct gesture categories, encompassing facial displays and hand movements. Within the facial expressions category, the features capture behaviors such as general facial expressions, eyebrow movements, eye movements, mouth openness, lip movements, and head movements. These encompass the behaviors shown in Fig. 1 for both individuals speaking truthfully and individuals engaging in deceptive behavior.

On the other hand, second major category encompasses gestures performed with the hands. This includes hand movements and hand trajectories, as shown in Fig. 1. These features collectively provide valuable insights into the non-verbal cues during both deceptive and truthful interactions.

Analysis of Feature Contribution We applied the chi-square method to identify the most significant features of facial expressions. The chi-square method is a statistical technique used to determine the relationship between variables and assess their dependence [16]. In our analysis, we applied the chi-square method to examine the association between different features and the classification of lying and truthful behaviors. Fig. 3 visualizes the results of this analysis, highlighting the most significant features. Specifically, the features “lips up,” “frown,” “lips down,” and “lips retracted” are found to be the most important in distinguishing between lying and truthful behaviors.

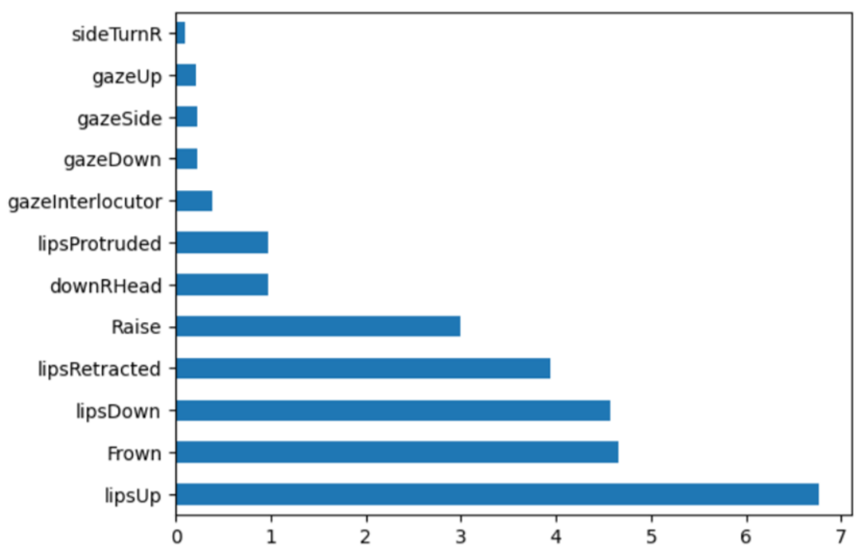

Fig. 3. Most significant non-verbal features

3.3 Methodological Analysis

Our designed dashboard encompasses ML and DL models’ performance analysis for lie detection, consisting of two parts: the back end and the front end. In the back-end section, we integrated the dataset and implemented various ML and DL techniques. Following that, we examined the distributions of facial expressions between individuals who were lying and those who were truthful. Finally,

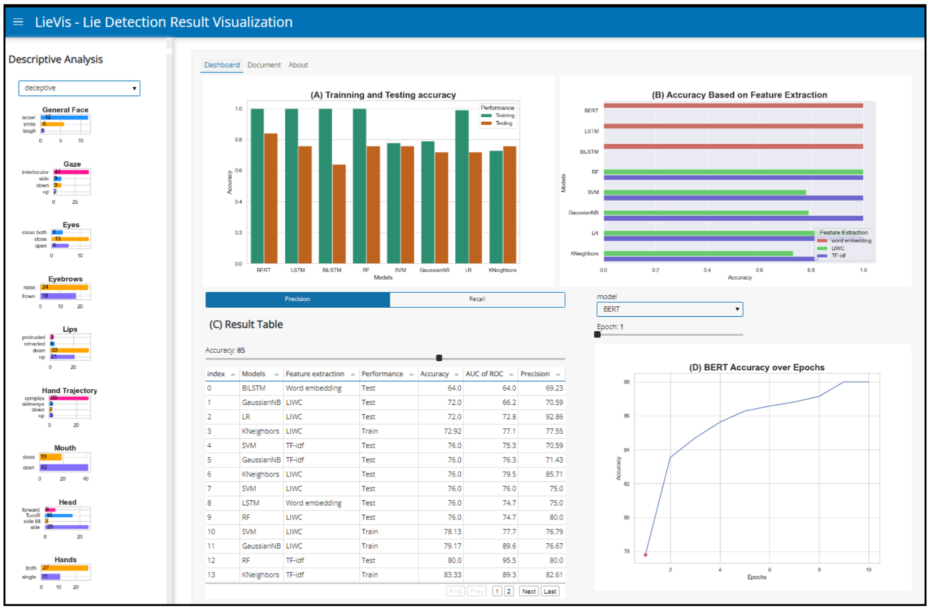

Fig. 4. Interactive visualization dashboard for Lie Detection, showcasing multifaceted detection and interpretation methods

we developed *LieVis*, which presents the results and identifies the method that surpasses others in terms of lie detection. This comprehensive analysis provides valuable insights into the effectiveness of different techniques and assists in identifying the most reliable approach for lie detection. Our visual dashboard comprises several graphs such as bar graph, a line graph, a horizontal bar chart, and a result table. In summary, our study followed a two-step approach to construct the framework:

1) Identification: Initially, we employed a range of ML and DL techniques to analyze lying behaviors.

2) Implementation: Subsequently, we developed a dashboard that includes the performance, accuracy, and precision of each model.

3.4 Visual Dashboard

We developed an interactive visualization dashboard specifically designed for lie detection. This dashboard incorporates a variety of charts and visualizations to facilitate the analysis and interpretation of the lie detection results. Our visual dashboard design includes a comprehensive range of plots to enhance the analysis and understanding of lie detection results. These plots consist of 1) a bar chart of training and testing accuracy which showcases the accuracy of each lie detection model during both the training and testing phases. It allows users to compare the performance of different models and determine their effectiveness in accurately detecting lies. 2) A horizontal bar chart of feature extraction which presents a comparison of different feature extraction techniques used in the process. It provides a clear visualization of the effectiveness and contribution of each technique in identifying deceptive or truthful behaviors. 3) Then, the precision and recall alternative results table displays precision and recall metrics for the lie detection models. And, lastly 4) responsive accuracy curve: this plot in our visual dashboard is a responsive accuracy curve that includes a drop-down menu and an epoch meter. The drop-down menu allows us to select a specific model that we are implementing for lie detection. Once a model is chosen, the accuracy curve updates accordingly, displaying the accuracy values at different epochs.

4 Performance Analysis

In this section, we present a comprehensive performance analysis of various DL and ML models for lie detection and a set of commonly used metrics, including accuracy, recall, precision, and ROC-AUC score. To assess the performance of our models, we employed these common metrics in binary classification tasks:

Table 3. Comparing the performance of DL models: We evaluated BERT (Bidirectional Encoder Representations from Transformers) and LSTM (Long Short-Term Memory). Based on our observations, the BERT model exhibited superior performance for the transcription dataset. On the other hand, the LSTM model showed lower performance, primarily due to the limited size of the dataset.

Model	**Training performances**				**Testing performances**			
	Accuracy	**Precision**	**Recall**	**Auc Score**	**Accuracy**	**Precision**	**Recall**	**Auc Score**
BERT	100	100	100	100	84	100	69.23	84.6
LSTM	100	100	100	100	76	75	85.71	74.7
BiLSTM	100	100	100	100	64	69.23	64.23	64

1. Accuracy: Accuracy is a measure of how correctly a classification model predicts the labels or classes of the input data. It is calculated as the ratio of the number of correct predictions to the total number of predictions. It is determined using the formula shown below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2. Precision: Precision is a measure of how many of the positively predicted instances are actually positive. It focuses on the correctness of the positive predictions made by the model. The calculation can be done using the equation for precision below.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Table 4. Performance evaluation with LIWC features: LIWC is a software tool used to extract linguistic and textual characteristics from text data. These features encompass various aspects such as word categories, linguistic dimensions, and psychological constructs. By incorporating LIWC features into our analysis, we gained valuable insights into the language patterns and psychological aspects present within the text data.

Model	Training performances				Testing performances			
	Accuracy	Precision	Recall	Auc Score	Accuracy	Precision	Recall	Auc Score
RF	100	100	100	100	76	80	66.67	74.7
SVM	78.13	76.79	84.31	77.7	76	75	75	76
GaussianNB	79.17	76.67	88.46	89.6	72	70.6	85.71	66.2
LR	98.96	98.04	100	100	72	92.86	68.42	72.8
KNeighbors	72.92	77.55	71.7	77.1	76	92.86	54.54	79.5

3. Recall: Recall, also known as sensitivity or true positive rate, is a measure of how many of the actual positive instances are correctly predicted by the model. It focuses on the ability of the model to identify positive instances.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Table 5. Performance Evaluation of ML Models with TF-IDF Features: TF-IDF features represent the importance of terms within a document collection, taking into account both term frequency (TF) and inverse document frequency (IDF). These features provide a numerical representation that captures the uniqueness and significance of terms for text analysis.

Model	Training performances				Testing performances			
	Accuracy	Precision	Recall	Auc Score	Accuracy	Precision	Recall	Auc Score
RF	100	100	100	100	80	80	85.71	95.5
SVM	100	100	100	100	76	70.59	92.31	75.3
GaussianNB	100	100	100	100	76	71.43	83.33	76.3
LR	100	100	100	100	84	100	71.43	95.5
KNeighbors	83.33	82.61	82.61	89.3	84	92.31	80	85

4. ROC-AUC Score: The AUC score is a summary metric derived from the ROC curve. It represents the area under the curve, ranging from 0 to 1. A higher AUC score indicates better model performance, with 1 being the highest achievable score.

5 Results and Discussion

In this section, we present the findings from various DL and ML-based approaches used for lie detection utilizing real-life trial court data. Leveraging the performance of these methods, we introduce *LieVis*, a novel interactive system designed to assist individuals dealing with liars and researchers in analyzing deceitful behavior. The dashboard features three tabs: Dashboard, Documentation, and About. The sidebar includes details about *LieVis*. The Dashboard tab encompasses our interactive dashboard, which provides an integrated interface for various functionalities and graphs. The dashboard, as illustrated in Fig. 4, consists of four distinct sections that offer the following functionalities:

- **First,** in section A, the bar graph illustrates the testing and training accuracies obtained from multiple ML and DL models. For testing purposes, 20% of the data was randomly selected, while the remaining 80% was utilized for training. The training and testing results of each model are presented for comparative analysis. This visualization aids users in comprehending the performance of each model throughout both the training and testing phases. In the training phase, BERT, LSTM, and BiLSTM achieved remarkable accuracies of 100%, 100%, and 100% respectively, as indicated in Table 3. Conversely, during the testing phase, accuracies of 84%, 76%, and 64% were obtained. Notably, BERT outperformed the other models in terms of testing accuracy. The analysis of these accuracies provides insights into the effectiveness and reliability of *LieVis*.
- **Second,** section B of the visualization dashboard presents a horizontal bar chart that illustrates the performance of various ML and DL models based on different feature extraction techniques. This comparison aids in identifying the most effective feature extraction approach for detecting lying. In our study, we employed three feature extraction techniques: word embedding, LIWC, and TF-IDF. The bar graph displays the performance results of each model, typically measured by a specific metric such as accuracy, indicated by the height of each bar. The training phase results of ML models utilizing TF-IDF feature extraction are presented in Table 5. RF, SVM, GaussianNB, LR, and KNeighbors achieved accuracies of 100%, 100%, 100%, 100%, and 83.33% respectively. Additionally, Table 4 showcases the accuracies of ML models using LIWC. Among the LIWC models, RF exhibited the highest training accuracy, whereas RF, SVM, Gaussian NB, and LR attained the highest accuracies when employing the TF-IDF technique. Hence, RF exhibits superior performance for both feature extraction methods.
- **Third,** in section C, a result table is presented, displaying precision and recall values for our chosen ML and DL models, as illustrated in Fig. 4. Precision and recall are commonly used metrics to assess the performance of a classification model. In the accompanying table, each row corresponds to a specific model, while the columns indicate the precision and recall values associated with that model.
- **Lastly,** in section D, an interactive accuracy curve enables users to explore the model and epoch-wise accuracy. Users can utilize the search field to select a specific model. Upon selecting the desired model, the line graph dynamically displays the accuracy of that model across a specific number

of iterations. This feature allows users to analyze the performance of the selected model over time.

5.1 User Study

In order to gain deeper insights into the efficacy of *LieVis*, we conducted an experimental assessment using a user study. Our objective was to investigate how real users engaged with the dashboard and reacted to the system, employing diverse inputs and displaying different perspectives. For our study, we enlisted the participation of five individuals, including two females and three males. Each participant had prior knowledge of the fundamental concepts of data visualization. They were introduced to the system and were asked to evaluate its performance, providing feedback accordingly. It is important to note that the participants willingly volunteered for the study and did not receive any form of compensation for their involvement.

6 Conclusion

As lying becomes increasingly prevalent in every field, there are ample opportunities to explore lie detection and develop comprehensive systems to address this issue. In this study, we introduced a web-based interactive visualization dashboard called *LieVis*, specifically designed to enable comprehensive exploration of results obtained from various ML and DL techniques. *LieVis* provides users with the capability to delve deeply into ML and DL results, facilitating a thorough analysis and understanding of the data. The techniques we have showcased play a significant role in enhancing the effectiveness of the lie detection system. By combining ML, DL, and Vis we have not only demonstrated the feasibility of utilizing AI for the development of automatic lie detection systems but also showcased its superiority over various other approaches.

However, it is crucial to acknowledge the variability of facial expressions among individuals, which makes it challenging to achieve the utmost accuracy solely based on facial expressions. Therefore, in future studies, our focus will be on enhancing accuracy by incorporating an increasing number of gestures alongside facial expressions, as they can provide more precise results. Additionally, it is important for future work to tackle data deficiencies and address annotation biases in order to enhance the accuracy and robustness of the system. One potential direction to explore is the integration of various classification methods into a hybrid approach, which holds the potential to further enhance performance and improve the overall effectiveness of the system.

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