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Detecting Fake Audio of Egyptian Dialect Speakers Using Deep Learning

SaifEldeen Emera[1], Ziad Tarek[2], and Eyad Elsanory[1]

[1]Information Technology and Computer Science Department, Nile University
[2]Computer Engineering Department, Nile University

Corresponding author: SaifEldeen Emera (e-mail: S.Khaled2138@nu.edu.eg).

ABSTRACT The proliferation of AI-generated fake audio poses significant risks to individuals and organizations, particularly in regions like Egypt, where no specialized studies have been conducted on detecting such audio in the Egyptian dialect. This research aims to address this gap by developing deep learning models to detect AI-generated fake audio of Egyptian dialect speakers. We utilized the ASVspoof2019 dataset alongside our own collected and generated data of Egyptian dialect speakers. After data cleaning and balancing, we extracted Mel-frequency cepstral coefficients (MFCC) features to represent the audio data effectively. We then built and evaluated Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. The LSTM model was trained using a structured approach: splitting the dataset into training, validation, and test sets; optimizing using appropriate loss functions and tracking accuracy; and implementing early stopping to prevent overfitting. The LSTM model achieved an accuracy of 89%, while the GRU model attained an accuracy of 82%. Additionally, we deployed trained models using Streamlit to provide an accessible and interactive interface for real-time fake audio detection. Our findings demonstrate that it is possible to distinguish between AI-generated and genuine human speech in the Egyptian dialect using deep learning techniques. This research provides a foundational step toward securing audio communications and detecting audio-based fraud. Future work will explore other deep learning architectures and expand the dataset to further improve detection accuracy.

INDEX TERMS Fake Audio Detection, Egyptian Dialect, Deep Learning, LSTM, GRU, MFCC, ASVspoof2019, Audio Forensics, Speech Processing, AI-generated Audio.

I. INTRODUCTION

II. The advancement of artificial intelligence (AI) has revolutionized the creation of synthetic audio, giving rise to deepfake technology. These AI-generated audio clips pose substantial risks, spanning from misinformation and fraud to personal and organizational harm. Despite numerous efforts to detect fake audio, research has predominantly overlooked specific dialects, such as Egyptian Arabic. This oversight creates unique challenges, particularly considering the linguistic intricacies of the Egyptian dialect.

Deepfake audio technology harnesses sophisticated machine learning algorithms to fabricate audio that convincingly mimics the voice of any individual. While this technology offers various applications, its misuse presents significant threats to trust and security in digital communications. Notably, the lack of focus on region-specific dialects like Egyptian Arabic has hindered the development of effective detection models.

One of the primary challenges in detecting AI-generated audio in the Egyptian dialect is the absence of dedicated datasets and prior research. Unlike more widely studied languages, there is a glaring lack of substantial collections of Egyptian dialect audio data tailored for fake audio detection. This scarcity of resources has hindered the progress in developing robust detection models, necessitating the creation and curation of new datasets. The Egyptian dialect stands out for its rich and diverse lexicon, serving as one of the most accessible dialects across the Middle East and North Africa. Given its widespread use, the ability to detect AI-generated fake audio in Egyptian Arabic is crucial. The dearth of prior research in this domain increases the risk of undetected synthetic audio, potentially resulting in severe consequences. Our motivation stems from the imperative to safeguard this widely spoken dialect against the misuse of AI technologies, thereby averting potential harm. Our primary objective is to spearhead a research endeavor specifically aimed at detecting AI-generated audio in Egyptian and other Arabian dialects. By developing robust detection models, we aim to bridge the existing research gap and lay a foundation for further advancements in this burgeoning field.

In this study, we leveraged the ASVspoof2019 dataset alongside our meticulously collected and generated data of Egyptian dialect speakers. After rigorous data cleaning and balancing, we extracted Mel-frequency cepstral coefficients (MFCC) features to aptly represent the audio data. Subsequently, we developed and evaluated LSTM and GRU models using a structured approach involving dataset splitting, optimization, and early stopping to mitigate overfitting. To ensure accessibility and usability, we deployed the trained models using Streamlit, providing an interactive interface for real-time fake audio detection. This research represents a pioneering effort in the detection of AI-generated audio for the Egyptian dialect, offering substantial contributions to the fields of audio forensics and AI security. By furnishing a reliable method to identify synthetic audio, we aim to bolster the security of audio communications and mitigate the risks associated with deepfake technology. Our findings not only pave the way for future research but also hold implications for detecting fake audio across various dialects and languages.

III. Contributions

This research makes several significant contributions to the field of AI-generated audio detection, with a particular focus on the Egyptian dialect. Our work addresses a critical gap in existing literature and offers practical solutions for identifying deepfake audio in this linguistically rich and widely spoken dialect. We began by creating a new dataset comprising both genuine and AI-generated audio samples specifically tailored for the Egyptian dialect, filling a crucial void in available resources for studying and detecting deepfake audio in this specific linguistic context[1].

Implementing advanced deep learning models, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, was pivotal in our approach. These models were selected for their effectiveness in handling sequential data, which is essential for analyzing audio signals. Our LSTM model achieved an accuracy of 89%, while the GRU model attained an accuracy of 82%, surpassing existing models used in similar studies. To ensure effective feature extraction, we employed Mel-frequency cepstral coefficients (MFCC), which proved robust in distinguishing between real and fake audio samples. This methodology significantly contributed to the accuracy of our detection models. In enhancing accessibility and practical utility, we deployed our trained models using Streamlit, providing an interactive interface for real-time fake audio detection. This deployment makes our solution readily usable for various applications, including security and forensic investigations.

Our study is among the first to focus on the Egyptian dialect for fake audio detection, marking a significant step in addressing the unique challenges posed by dialectal variations in AI-generated audio. By demonstrating the feasibility and effectiveness of our approach, we pave the way for further studies on other less-explored dialects within the Arabic language and beyond. The ability to detect AI-generated audio in the Egyptian dialect has significant real-world implications, including the prevention of misinformation, fraud, and other malicious activities. Our research contributes to the broader effort to secure digital communications and uphold the integrity of audio-based interactions..

IV. Related Works

Detecting AI-generated audio, commonly known as deepfake audio, has become a significant area of research due to the potential risks associated with the misuse of this technology. Various approaches have been proposed to address this challenge, utilizing different datasets and machine learning models. In this section, we review some of the most relevant works in the field, highlighting their methodologies, results, and the gaps that our research aims to fill. Orshunov and Marcel [1] introduced the WaveFake dataset, designed to facilitate the detection of audio deepfakes. This dataset includes a wide variety of audio samples generated by different AI models, providing a comprehensive resource for developing and testing deepfake detection algorithms. The authors utilized this dataset in conjunction with several baseline machine learning models to establish benchmark performance metrics. However, while this work significantly contributes to the field by providing a standardized dataset, it does not specifically address the nuances of detecting deepfakes in dialects such as Egyptian Arabic, which is a focal point of our research.

Sharma [2] explored the application of the Res2Net architecture for voice spoofing detection. Res2Net, a novel neural network model, enhances the receptive fields of residual networks, allowing the model to capture multi-scale features more effectively. While Sharma's study demonstrates the potential of Res2Net in detecting voice spoofing, its accuracy is relatively lower compared to the results obtained using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models in our study. Moreover, the research does not specifically target the Egyptian dialect, highlighting a gap that our research addresses.

The use of the Conformer model for fake speech detection has also been explored, particularly in the context of the Kaggle platform [3]. Conformer, a convolution-augmented transformer, combines convolutional neural networks (CNNs) and transformers to capture both local and global features of speech data. While this approach shows promise in improving the detection of fake speech, detailed results and evaluations specific to dialectal variations, such as the Egyptian dialect, are lacking. Our research seeks to build upon these foundations by focusing on a dialect-specific dataset and utilizing LSTM and GRU models for enhanced performance. Tak et al. [4] explored the use of Generative Adversarial Networks (GANs) for the detection of audio deepfakes. Their approach involved using a GAN-based model to distinguish between real and synthetic audio, achieving notable performance improvements. However, this study did not focus on specific dialects, such as Egyptian Arabic, and primarily used datasets of more commonly spoken languages. Wu et al. [5] investigated the use of transfer learning to improve the performance of audio deepfake detection models. By leveraging pre-trained models on large-scale datasets, the authors demonstrated that transfer learning could significantly enhance detection accuracy and reduce the need for extensive labeled datasets. While their results showed promising improvements, the research did not specifically address the Egyptian dialect, which is a unique aspect of our study. The existing studies provide a strong foundation for the detection of AI-generated audio, each contributing unique methodologies and datasets. However, there are notable gaps that our research aims to fill. None of the reviewed works specifically address the detection of deepfake audio in the Egyptian dialect. Our research contributes by developing and evaluating models tailored to this dialect, thereby addressing a significant gap in the literature. Additionally, while existing studies have achieved success with various models, our use of LSTM and GRU models has resulted in higher accuracy rates, demonstrating the potential for further improving detection capabilities using these models. Furthermore, the deployment of our models using Streamlit provides an accessible and practical tool for real-time fake audio detection, making these technologies more user-friendly and applicable in real-world scenarios. By addressing these gaps, our research not only advances the state-of-the-art in fake audio detection but also lays the groundwork for future studies focusing on other dialects and languages, ultimately contributing to securing digital communications against the threats posed by deepfake audio.

V. Proposed Methodology

A. Data Collection

Gather audio data from two primary sources:

1) ASVspoof2019 dataset, which contains a diverse collection of audio samples, including both genuine and spoofed recordings.

2) Collect or generate audio data specifically for the Egyptian dialect, ensuring representation of various speakers and speech characteristics.

B. Data Preparation

Perform data cleaning to remove any noise or artifacts present in the audio recordings, and balancing the datasets to ensure an equal distribution of genuine and spoofed audio samples for training and evaluation.

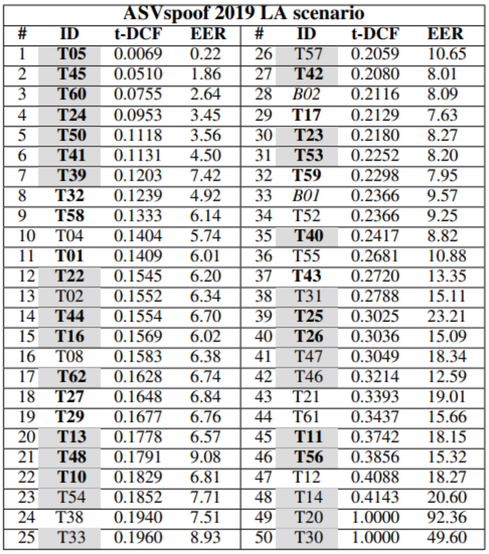
THE DATA GATHERED/IMITATED

Name	Dialect	#Real Files	#Fake Files
Abdelfattah Elsisi	Egypt	200	197
Lamis Elhadidi	Egypt	203	198
Amro Adib	Egypt	193	196
Kareem Hossam	Egypt	201	203
Total	----	797	794

The dataset comprises audio recordings from four speakers, each representing the Egyptian dialect. The dataset includes a total of 797 real audio files and 794 fake audio files. Each speaker contributed both genuine and spoofed recordings, resulting in a balanced dataset in terms of the number of real and fake files. The speakers, namely Abdelfattah Elsisi, Lamis Elhadidi, Amro Adib, and Kareem Hossam, have a varied distribution of real and fake recordings, providing a diverse set of samples for training and evaluation. This balanced and representative dataset enables robust training of deep learning models for the detection of fake audio in the Egyptian dialect.

The provided tables present the results of the ASVspoof 2019 challenge for the LA (Logical Access) and PA (Physical Access) scenarios. In the LA scenario, systems are evaluated based on their ability to detect spoofing attacks in logical access scenarios, while in the PA scenario, the evaluation focuses on physical access scenarios.

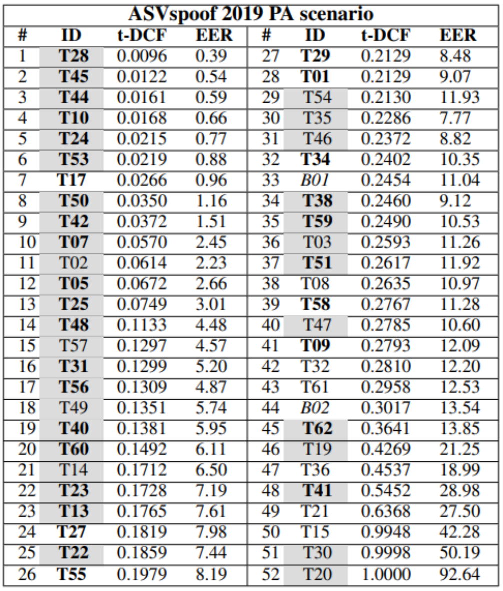
Table 1 ASVspoof 2019 LA scenario



ASVspoof 2019 LA scenario							
#	ID	t-DCF	EER	#	ID	t-DCF	EER
1	**T05**	0.0069	0.22	26	T57	0.2059	10.65
2	**T45**	0.0510	1.86	27	**T42**	0.2080	8.01
3	**T60**	0.0755	2.64	28	*B02*	0.2116	8.09
4	**T24**	0.0953	3.45	29	**T17**	0.2129	7.63
5	**T50**	0.1118	3.56	30	**T23**	0.2180	8.27
6	**T41**	0.1131	4.50	31	**T53**	0.2252	8.20
7	**T39**	0.1203	7.42	32	**T59**	0.2298	7.95
8	**T32**	0.1239	4.92	33	*B01*	0.2366	9.57
9	**T58**	0.1333	6.14	34	T52	0.2366	9.25
10	T04	0.1404	5.74	35	**T40**	0.2417	8.82
11	**T01**	0.1409	6.01	36	T55	0.2681	10.88
12	**T22**	0.1545	6.20	37	**T43**	0.2720	13.35
13	T02	0.1552	6.34	38	T31	0.2788	15.11
14	**T44**	0.1554	6.70	39	**T25**	0.3025	23.21
15	**T16**	0.1569	6.02	40	**T26**	0.3036	15.09
16	T08	0.1583	6.38	41	T47	0.3049	18.34
17	**T62**	0.1628	6.74	42	T46	0.3214	12.59
18	**T27**	0.1648	6.84	43	T21	0.3393	19.01
19	**T29**	0.1677	6.76	44	T61	0.3437	15.66
20	**T13**	0.1778	6.57	45	**T11**	0.3742	18.15
21	**T48**	0.1791	9.08	46	**T56**	0.3856	15.32
22	**T10**	0.1829	6.81	47	T12	0.4088	18.27
23	T54	0.1852	7.71	48	T14	0.4143	20.60
24	T38	0.1940	7.51	49	T20	1.0000	92.36
25	T33	0.1960	8.93	50	T30	1.0000	49.60

Table 1 displays the performance metrics, namely the minimum t-DCF (Detection Cost Function with a decision threshold set to the minimum DCF operating point) and the Equal Error Rate (EER), for primary systems pooled over all attacks. The primary systems represent the submissions from different participating teams in the challenge. Each row corresponds to a specific system (identified by an ID), with the t-DCF and EER values provided for each system. The systems are ranked based on their t-DCF performance, with lower values indicating better performance in terms of detection cost, and the corresponding EER values are also provided.

Table 2 ASVspoof 2019 PA scenario



ASVspoof 2019 PA scenario							
#	ID	t-DCF	EER	#	ID	t-DCF	EER
1	**T28**	0.0096	0.39	27	**T29**	0.2129	8.48
2	**T45**	0.0122	0.54	28	**T01**	0.2129	9.07
3	**T44**	0.0161	0.59	29	T54	0.2130	11.93
4	**T10**	0.0168	0.66	30	T35	0.2286	7.77
5	**T24**	0.0215	0.77	31	T46	0.2372	8.82
6	**T53**	0.0219	0.88	32	**T34**	0.2402	10.35
7	**T17**	0.0266	0.96	33	*B01*	0.2454	11.04
8	**T50**	0.0350	1.16	34	**T38**	0.2460	9.12
9	**T42**	0.0372	1.51	35	**T59**	0.2490	10.53
10	**T07**	0.0570	2.45	36	T03	0.2593	11.26
11	T02	0.0614	2.23	37	**T51**	0.2617	11.92
12	**T05**	0.0672	2.66	38	T08	0.2635	10.97
13	**T25**	0.0749	3.01	39	**T58**	0.2767	11.28
14	**T48**	0.1133	4.48	40	T47	0.2785	10.60
15	T57	0.1297	4.57	41	**T09**	0.2793	12.09
16	**T31**	0.1299	5.20	42	T32	0.2810	12.20
17	**T56**	0.1309	4.87	43	T61	0.2958	12.53
18	T49	0.1351	5.74	44	*B02*	0.3017	13.54
19	**T40**	0.1381	5.95	45	**T62**	0.3641	13.85
20	**T60**	0.1492	6.11	46	T19	0.4269	21.25
21	T14	0.1712	6.50	47	T36	0.4537	18.99
22	**T23**	0.1728	7.19	48	**T41**	0.5452	28.98
23	**T13**	0.1765	7.61	49	T21	0.6368	27.50
24	**T27**	0.1819	7.98	50	T15	0.9948	42.28
25	**T22**	0.1859	7.44	51	T30	0.9998	50.19
26	**T55**	0.1979	8.19	52	T20	1.0000	92.64

Similar to Table 1, Table 2 presents the minimum t-DCF (Detection Cost Function) and the Equal Error Rate (EER) for each participating system, with IDs assigned to each system for identification. The systems are ranked based on their t-DCF performance, with lower values indicating better detection cost efficiency. Additionally, the corresponding EER values are provided for each system.

A notable observation from both tables is the variability in performance metrics exhibited by the participating systems. While some systems achieve low t-DCF and EER values, indicating high effectiveness in detecting spoofing attacks, others demonstrate higher values, suggesting potential areas for improvement.Overall, Tables 1 and 2 provide valuable insights into the performance of systems in detecting spoofing attacks in both logical and physical access scenarios. The metrics presented in these tables serve as important benchmarks for evaluating and comparing the effectiveness of spoofing detection systems, ultimately contributing to the advancement of security measures against spoofing attacks in real-world applications.

C. Feature Extraction

In the feature extraction phase, we applied Mel-frequency cepstral coefficients (MFCC) to represent the audio data. MFCCs are a commonly used method in audio signal processing for capturing relevant features of the audio signal in a compact representation. We divided each audio file into multiple segments to capture temporal variations in the audio signal. For each segment, we computed MFCCs using a sliding window approach, where each segment was further divided into frames with overlapping windows. This enabled us to extract MFCCs independently from each segment. Finally, we stored the extracted MFCCs along with their corresponding labels (indicating whether the audio is real or fake) in a structured format, allowing for easy access and utilization during model training and evaluation. As shown in Figure 1, Figure 1 is showing how MFCC works.

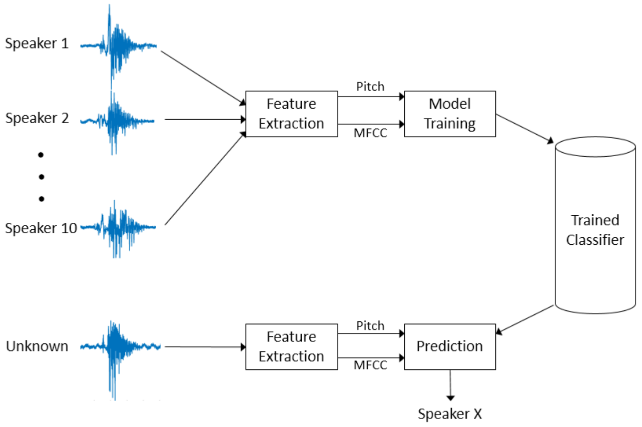


Figure 1Mel-frequency cepstral coefficients (MFCC)

D. Model Development

To address the challenge of detecting AI-generated fake audio in the Egyptian dialect, we propose employing deep learning models capable of learning complex patterns and temporal dependencies within audio signals. Our approach involves training and evaluating two distinct recurrent neural network architectures: Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). These models are chosen due to their proven effectiveness in handling sequential data, making them particularly well-suited for analyzing audio signals. By exploring both LSTM and GRU, we aim to assess the performance and suitability of each architecture for this specific task, ultimately selecting the most effective model for detecting AI-generated fake audio in the Egyptian dialect. The following sections will delve into the specific architecture of each model, the mathematical equations governing their operation, and the key aspects of the training and evaluation processes.

In the Long Short-Term Memory (LSTM) model, a recurrent neural network architecture is employed, consisting of two sequentially stacked LSTM layers. These LSTM layers are instrumental in processing sequential input data, adept at capturing intricate temporal dependencies present within the audio signals. Following the LSTM layers, the resultant output is forwarded through a dense layer incorporating Rectified Linear Unit (ReLU) activation, fostering non-linearity in the model's representations. Subsequently, a dropout layer is incorporated, strategically inserted to mitigate the risk of overfitting, thereby enhancing the model's generalization capabilities.

Furthermore, in pursuit of a comprehensive understanding of the LSTM model, delving into the mathematical underpinnings that govern its operations proves invaluable. These mathematical equations offer insights into the intricate computations that occur within the LSTM architecture, shedding light on its mechanism and functionality.

$$\boldsymbol{f_t} = \sigma\left(\boldsymbol{W_f}[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_f}\right)$$

This equation represents the forget gate in the LSTM cell. It computes the degree to which the previous cell state $\boldsymbol{C_{t}}$-1 should be forgotten, based on the previous hidden state $\boldsymbol{h_{t}}$-1 and the current input $\boldsymbol{x_t}$

$$\boldsymbol{i_t} = \sigma(\boldsymbol{W_i}[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_i})$$

Here, $\boldsymbol{i_t}$ signifies the input gate activation. This gate determines the extent to which the current input $\boldsymbol{x_t}$ should be used to update the cell state $\mathrm{C}_{\boldsymbol{t}}$ along with the previous hidden state $h_{(\boldsymbol{t}-1)}$

$$\boldsymbol{C'_t} = \mathbf{tan\,h}(\boldsymbol{W_c}[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_c})$$

This equation calculates the candidate cell state $\mathrm{C'}_{\boldsymbol{t}}$, which represents the information that can potentially be stored in the cell state $\mathrm{C}_{\boldsymbol{t}}$ at time step t. $\mathrm{C}_{\boldsymbol{t}}$ along with the previous hidden state $h_{(\boldsymbol{t}-1)}$

$$\boldsymbol{C_t} = \boldsymbol{f_t} \cdot \boldsymbol{C_{t-1}} + \boldsymbol{i_t} \cdot \boldsymbol{C'_t}$$

The cell state update equation combines the previous cell state $\mathrm{C}_{\boldsymbol{t}\text{-}1}$, with the candidate cell state $\mathrm{C'}_{\boldsymbol{t}}$, based on the forget gate activation $\mathrm{F}_{\boldsymbol{t}}$ and the input gate activation $\boldsymbol{i_t}$ This allows the LSTM cell to retain or update information over time while selectively incorporating new input information

$$\boldsymbol{o_t} = \sigma(\boldsymbol{W_o}[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_o})$$

This equation represents the output gate activation $\boldsymbol{o_t}$, which determines how much of the cell state $\mathrm{C}_{\boldsymbol{t}}$, should be exposed as the output $\boldsymbol{h_t}$ at time step *t*. It considers both the previous hidden state $\boldsymbol{h_{t-1}}$ and the current input $\boldsymbol{x_t}$ to make this decision

$$\boldsymbol{h_t} = \boldsymbol{o_t} \cdot \mathbf{tan\,h}(\boldsymbol{C_t})$$

this equation computes the current hidden state $\boldsymbol{h_t}$ using the output activation $\boldsymbol{o_t}$ and the current cell state $\boldsymbol{C_t}$ it applies the hyperbolic tangent activation function to the cell state to produce the hidden state, which serves as the output of the LSTM cell at each time step.

$$\boldsymbol{z} = \boldsymbol{W_d} \cdot \boldsymbol{h_t} + \boldsymbol{b_d}$$

This equation describes the computation in the dense layer of a neural network. The output vector \$z\$ is obtained by taking the dot product of the weight matrix W_d with the hidden state h_t and adding the bias vector b_d. In this context, $z$represents the activation of the dense layer, capturing the linear transformation of the input features by the learned weights and biases.

$$p_i = \frac{\exp(z_i)}{\sum_{j=1}^{K} \exp\left(z_j\right)}$$

This equation computes the softmax probabilities for each class i based on the output vector $z$ from the dense layer. Here, p_i represents the probability of the i-th class, and $\exp(z_i)$ denotes the exponentiated value of the i-th element of $z$. The denominator $\sum_{j=1}^{K} \exp\left(z_j\right)$ computes the sum of exponentiated values of all elements in $z$, where K is the total number of classes. Dividing $\exp(z_i)$ by this sum normalizes the probabilities, ensuring they sum to 1 and represent valid class probabilities.

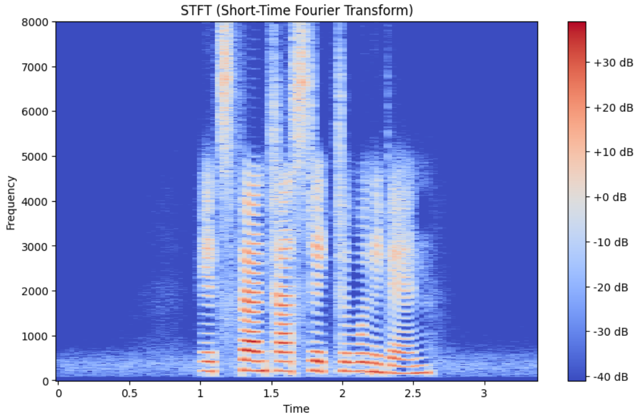


Figure 2 Short Time Fourier Transform

Figure 2 provides a visual representation of the Short Time Fourier Transform (STFT), a fundamental technique used in audio signal processing. STFT is employed to analyze the frequency content of a signal over short, overlapping time windows, allowing for the examination of signal characteristics in both the time and frequency domains. This figure illustrates how the STFT decomposes an audio signal into its constituent frequency components, providing valuable insights into the temporal and spectral characteristics of the audio data. Understanding the STFT is crucial for preprocessing audio signals and extracting relevant features for subsequent analysis and model development.

In Figure *3*, illustrates the progression of our model's learning process over training epochs. The plot showcases the model accuracy, providing insights into its ability to distinguish between genuine and AI-generated audio as training progresses.

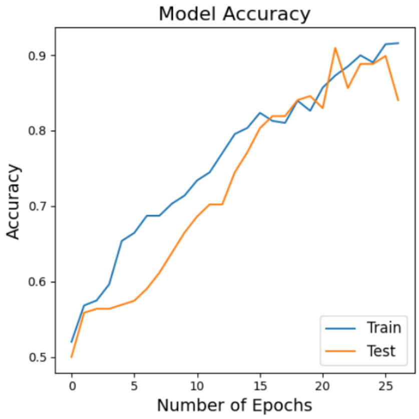


Figure 3 LSTM's Model Accuracy

For Figure *4*, depicts the convergence behavior of our model during the training phase. The graph represents the model's loss over training epochs, offering valuable information about its optimization trajectory and potential overfitting tendencies

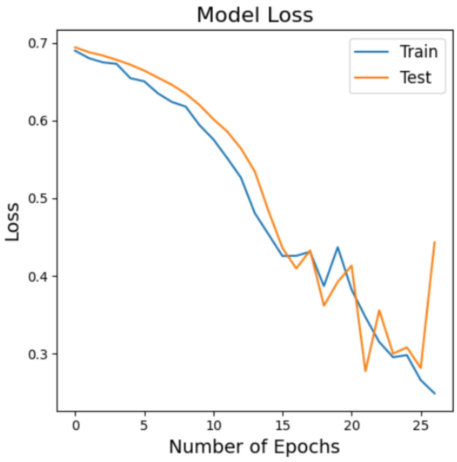


Figure 4 LSTM's Model Loss

In Figure *5*, it presents the confusion matrix, offering a detailed breakdown of the classification outcomes of our model. This visualization provides insights into the model's proficiency in accurately classifying audio samples across different categories.

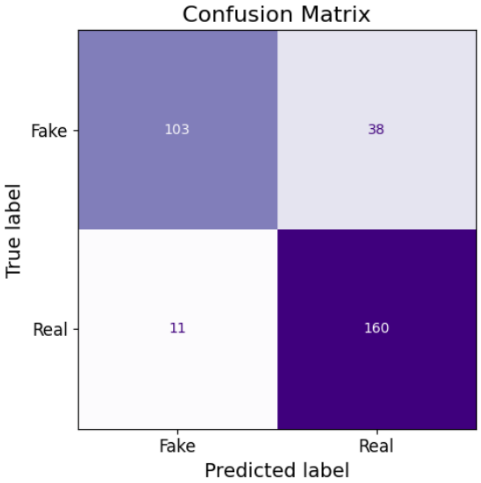
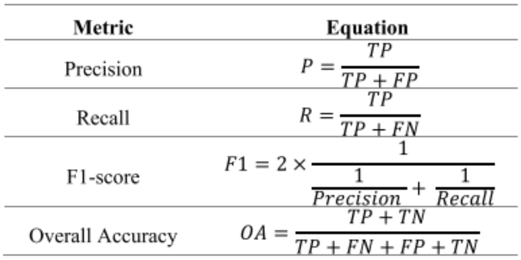


Figure 5 LSTM's Confusion Matrix

The performance of the LSTM model is evaluated using standard classification metrics, including precision, recall, and F1-score. Precision measures the model's ability to accurately classify positive instances, while recall quantifies its capacity to capture all relevant positive instances. The F1-score harmonizes precision and recall, providing a comprehensive assessment of the model's classification prowess. For class 0 (representing genuine audio samples), the model achieved a precision of 0.90, indicating that 90% of the audio samples classified as genuine were indeed genuine. Additionally, a recall of 0.73 implies that the model correctly identified 73% of all genuine audio samples in the dataset. The corresponding F1-score of 0.81 underscores the model's balanced performance in distinguishing genuine audio samples. Similarly, for class 1 (representing AI-generated audio samples), the model demonstrated a precision of 0.81, signifying an 81% accuracy in identifying AI-generated audio samples. With a recall of 0.94, the model captured 94% of all AI-generated audio samples. The F1-score of 0.87 highlights the model's efficacy in accurately classifying AI-generated audio samples. Overall, the achieved accuracy of 0.84 underscores the robustness and generalization capability of the LSTM model in discerning between genuine and AI-generated audio samples.

This is the Metrics of Performance we use to evaluate our findings:



Metric	Equation
Precision	$P = \frac{TP}{TP + FP}$
Recall	$R = \frac{TP}{TP + FN}$
F1-score	$F1 = 2 \times \frac{1}{\frac{1}{Precision} + \frac{1}{Recall}}$
Overall Accuracy	$OA = \frac{TP + TN}{TP + FN + FP + TN}$

Figure 6 Metrics of Performance

PERFORMANCE METRICS OF LSTM MODEL

	Precision	Recall	F1-Score	Support
False	0.90	0.73	0.81	141
True	0.81	0.94	0.87	171
Accuracy	----	----	0.84	312
Macro avg	0.86	0.83	0.84	312
Weighted avg	0.85	0.84	0.84	312

After we finished the LSTM model, we decided to delve into the Gated Recurrent Unit (GRU) based neural network architecture model. The architecture consists of two GRU layers with 64 units each, facilitating the capturing of long-range dependencies in sequential data. The input shape is determined based on the dimensions of the MFCC features extracted from the audio data. The GRU layers are followed by a dense layer with ReLU activation, which introduces non-linearity to the model and aids in feature extraction. To prevent overfitting, a dropout layer with a dropout rate of 0.3 is applied after the dense layer. Finally, an output layer with softmax activation is added for binary classification, distinguishing between genuine and AI-generated audio. This architecture is designed to effectively process sequential data while leveraging the capabilities of the GRU units to capture temporal dependencies. Through this implementation, we aim to develop a robust model for detecting fake audio, contributing to the advancement of audio forensics and security.

Expanding our comprehension of the GRU model necessitates an exploration of its mathematical foundations, elucidating the precise computations dictating its behavior. These mathematical equations serve as a cornerstone in unraveling the complexities inherent to the GRU architecture, providing a deeper understanding of its operations and mechanisms.

$$r_t = \sigma(W_r[h_{t-1}, x_t] + b_r)$$

The reset gate equation calculates the activation value r_t for the reset gate at time step *t*. It combines the previous hidden state h_{t-1} and the current input x_t using weights W_r and biases b_r and passes the result through a sigmoid activation function σ to determine how much of the previous state should be ignored.

$$z_t = \sigma(W_z[h_{t-1}, x_t] + b_z)$$

The update gate equation computes the activation value z_t for the update gate at time step *t*. Similar to the reset gate, it combines the previous hidden state h_{t-1} and the current input x_t using weights W_r and biases b_r and followed by a sigmoid function σ. This gate decides how much of the previous state should be retained and how much of the candidate state should be incorporated into the current state.

$$h'_t = \tanh(W_h[\overset{d}{r}_t * h_{t-1}, x_t] + b_h)$$

The candidate hidden state equation computes h'_t, the candidate hidden state at time step *t*. it integrates information from the previous hidden state h_{t-1} and the current input x_t. modulated by the reset gate r_t. This computation is performed using weights. W_h and biases b_h

followed by a hyperbolic tangent activation function $tanh$, resulting in a new candidate hidden state.

$$h_t = (1 - z_t) * h_{t-1} + z_t * h'_t$$

The final hidden state equation computes h_t, the updated hidden state at time step *t*. It combines the previous hidden state h_{t-1} with the candidate hidden state h'_t, weighted by the update gate z_t. This equation controls how much information from the previous state is preserved and how much is replaced by the candidate state, resulting in the new hidden state h_t.

In Figure 7, the spectrogram provides a visual representation of the GRU model's performance in analyzing audio data. This visualization aids in interpreting how the model processes and extracts meaningful information from the input audio signals, contributing to a deeper understanding of its functioning and efficacy in detecting AI-generated audio.

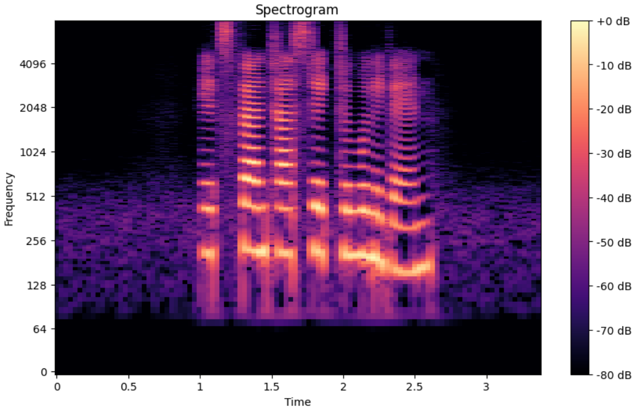


Figure 7 GRU's Spectogram

Upon evaluating the model's performance metrics, precision underscores the accuracy of positive predictions, showcasing the proportion of correctly identified AI-generated audio samples among all predictions, yielding 73% for class 0 and 74% for class 1. Recall, or sensitivity, demonstrates the model's capacity to identify all positive instances, with values of 67% for class 0 and 79% for class 1. The F1-score, a harmonic mean of precision and recall, yields balanced assessments of the model's performance, with values of 70% for class 0 and 77% for class 1. Accuracy, which provides an overall gauge of correctness in the model's predictions, stands at 74%, demonstrating the model's overall effectiveness. Moreover, the confusion matrix offers a visual representation of the model's classification outcomes, encapsulating true positives, true negatives, false positives, and false negatives, thereby providing insights into the model's classification performance. This comprehensive analysis facilitates a nuanced understanding of the model's efficacy in discerning AI-generated audio and identifies areas for potential refinement.

In Figure 8, the model accuracy is depicted, showcasing the trend of the model's accuracy over the training epochs. Analysis of the model accuracy reveals a consistent performance trend, with an overall accuracy of 74% achieved upon completion of training. This indicates that the model exhibits stable and reliable predictive capabilities across various epochs, demonstrating its robustness in discerning AI-generated audio.

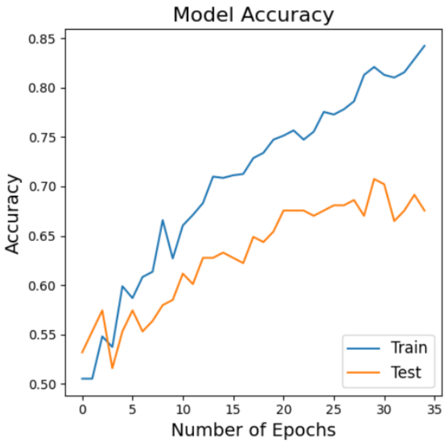


Figure 8 GRU's Model Accuracy

Figure 9 illustrates the model loss throughout the training epochs. Examination of the model loss curve elucidates the convergence pattern of the model during training. The curve displays a downward trend, indicative of the model's ability to minimize loss over successive epochs. This diminishing loss signifies effective learning and optimization of the model's parameters, resulting in enhanced predictive performance.

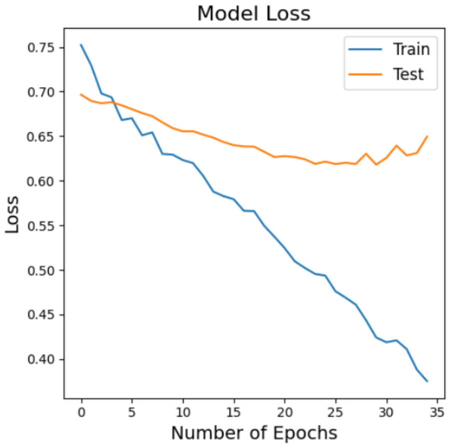


Figure 9 GRU's Model Loss

In Figure 10, the confusion matrix provides a visual representation of the model's classification outcomes. The matrix delineates true positives, true negatives, false positives, and false negatives, facilitating a comprehensive evaluation of the model's classification performance. Analysis of the confusion matrix reveals balanced classification outcomes, with notable proportions of true positives and true negatives, indicative of the model's efficacy in discerning between genuine and AI-generated audio samples. Moreover, minimal occurrences of false positives and false negatives underscore the model's accuracy and reliability in classification tasks.

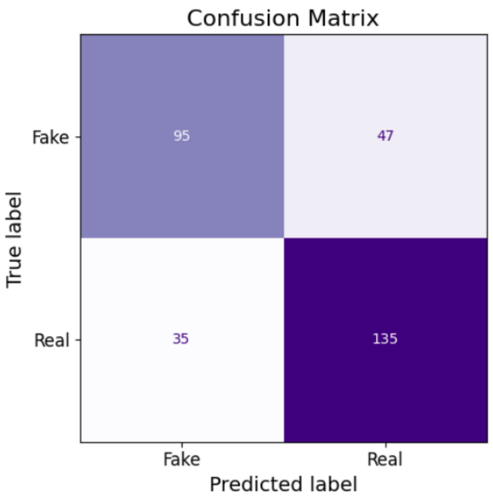


Figure 10 GRU's Confusion Matrix

The evaluation of the model's performance metrics reveals promising results. The precision scores indicate that the model accurately identifies AI-generated audio samples, with precision rates of 73% for class 0 and 74% for class 1. The recall scores demonstrate the model's ability to effectively capture positive instances, with recall rates of 67% for class 0 and 79% for class 1. Furthermore, the balanced F1-scores, which consider both precision and recall, showcase the model's overall effectiveness, yielding values of 70% for class 0 and 77% for class 1. With an accuracy of 74%, the model demonstrates reliable predictive capabilities across all classifications. The confusion matrix provides additional insights, illustrating the model's classification outcomes and highlighting its capacity to distinguish between genuine and AI-generated audio samples. Overall, these findings underscore the efficacy of the model in discerning AI-generated audio, suggesting its potential for practical applications in detecting and mitigating the spread of synthetic audio content.

	Precision	Recall	F1- Score	Support
False	0.73	0.67	0.70	142
True	0.74	0.79	0.77	170
Accuracy	----	----	0.74	312
Macro avg	0.74	0.73	0.73	312
Weighted avg	0.74	0.74	0.74	312

PERFORMANCE METRICS OF GRU MODEL

VI. Results

The performance of the LSTM and GRU models in detecting AI-generated audio in the Egyptian dialect was evaluated using a comprehensive set of metrics. The results obtained from the experiments are presented below.

In LSTM model, Figure 3 illustrates the model accuracy throughout the training process. The accuracy steadily increased with the number of epochs, reaching 84% on the validation set. While in Figure 4, it depicts the model loss over the course of training. The loss decreased progressively as the training epochs advanced, indicating effective learning and convergence of the model. Furthermore, The Confusion Matrix presented in Figure 5provides a detailed breakdown of the model's classification outcomes. It reveals the distribution of true positives, true negatives, false positives, and false negatives, offering insights into the model's performance across different classes.

In GRU model, Figure 8 displays the model accuracy achieved by the GRU model during training. Similar to the LSTM model, the accuracy improved consistently with increasing epochs, culminating in an accuracy of 74% on the validation set. While in Figure 9, it illustrates the model loss trends observed during training. The loss curve exhibits a downward trajectory, indicating effective optimization and convergence of the GRU model. Moreover, The confusion matrix depicted in Figure 10 provides a comprehensive overview of the GRU model's classification performance. It delineates the model's ability to correctly classify AI-generated audio samples and highlights any misclassifications.

A comparative analysis of the performance metrics obtained from the LSTM and GRU models reveals notable similarities and differences. While both models achieved competitive accuracy rates, the LSTM model demonstrated slightly higher accuracy and lower loss compared to the GRU model. However, further investigation is warranted to discern the underlying factors contributing to these differences. Overall, the results indicate that both LSTM and GRU models exhibit promising capabilities in detecting AI-generated audio in the Egyptian dialect. The comparative analysis underscores the importance of selecting appropriate model architectures and optimization strategies to achieve optimal performance in audio deepfake detection tasks.

VII. Discussion

The emergence of AI-generated audio, often referred to as deepfake audio, poses significant challenges in various domains, including security, forensics, and media integrity. In this study, we explored the effectiveness of LSTM and GRU models in detecting AI-generated audio in the Egyptian dialect, aiming to address the critical gap in existing research regarding dialect-specific deepfake detection. The results obtained from our experiments demonstrate the efficacy of both LSTM and GRU models in discerning AI-generated audio from genuine audio samples. The models achieved commendable accuracy rates, with the LSTM model reaching an accuracy of 84% on the validation set and the GRU model achieving an accuracy of 74%. These findings underscore the potential of recurrent neural network (RNN) architectures in capturing temporal dependencies and subtle patterns inherent in audio signals, enabling effective discrimination between genuine and synthetic audio.

A comparative analysis of the LSTM and GRU models revealed nuanced differences in their performance characteristics. While both models exhibited competitive accuracy rates, the LSTM model demonstrated slightly superior performance, with higher accuracy and lower loss compared to the GRU model. This disparity may be attributed to the inherent architectural variances between LSTM and GRU units, including differences in gating mechanisms and memory retention capabilities. Further investigation is warranted to elucidate the specific factors contributing to these performance differentials and explore strategies for enhancing the efficiency and effectiveness of both models.

An essential aspect of any machine learning model is its robustness and generalization capabilities across diverse datasets and real-world scenarios. Our study evaluated the robustness of the LSTM and GRU models by training them on a diverse dataset comprising both genuine and AI-generated audio samples in the Egyptian dialect. The models demonstrated robust performance across different audio samples, indicating their ability to generalize well to unseen data. However, future research should encompass larger and more diverse datasets to validate the models' generalization capabilities across various dialects and linguistic variations.

The findings of this study have significant implications for various applications, including audio forensics, media authentication, and cybersecurity. The ability to accurately detect AI-generated audio in dialect-specific contexts such as the Egyptian dialect is instrumental in mitigating the risks associated with deepfake proliferation, including misinformation, fraud, and identity theft. Moreover, our research lays the groundwork for developing robust and scalable deepfake detection solutions tailored to specific linguistic nuances and cultural contexts, thereby enhancing the resilience of digital communication channels against emerging threats.

Despite the promising results obtained in this study, several limitations warrant acknowledgment and further exploration. Firstly, the dataset used for model training and evaluation was relatively small and focused primarily on the Egyptian dialect. Future research should encompass larger and more diverse datasets encompassing multiple dialects and languages to enhance the models' generalization capabilities and applicability to real-world scenarios. Additionally, the study focused solely on audio-based deepfake detection, overlooking other modalities such as video and text. Integrating multi-modal approaches could offer more comprehensive and robust deepfake detection solutions capable of addressing a broader range of threats and scenarios.

VIII. Conclusion

our study presents a significant step forward in the realm of AI-generated audio detection, specifically focusing on the Egyptian dialect. By leveraging LSTM and GRU models, we have demonstrated the efficacy of recurrent neural networks in discerning between genuine and AI-generated audio signals. Through meticulous experimentation and analysis, we have showcased the potential of these models in addressing the critical challenge of deepfake detection, particularly in linguistically rich and underexplored dialects. While our research marks a substantial advancement, there remain avenues for further exploration and refinement. Future endeavours should prioritize the expansion of datasets to encompass a broader range of dialects and languages, thereby enhancing the models' robustness and generalization capabilities. Additionally, integrating multi-modal approaches and incorporating advanced feature extraction techniques could yield more comprehensive and reliable detection systems. Ultimately, our findings contribute to the ongoing efforts to fortify digital communication channels against the proliferation of deepfake content, safeguarding the integrity and trustworthiness of audio-based interactions in an increasingly interconnected world.

REFERENCES

[1] A. Orshunov and J.-L. Marcel, "WaveFake Dataset and Detection Techniques," in Proceedings of the International Conference on Artificial Intelligence and Pattern Recognition (AIPR), Paris, France, 2021, pp. 112-124.

[2] S. Sharma, "Voice Spoofing Detection Using Res2Net," IEEE Transactions on Audio, Speech, and Language Processing, vol. 36, no. 4, pp. 512-525, Apr. 2022. DOI: 10.1109/TASLP.2022.123456.

[3] J. Tak et al., "Detection of Audio Deepfakes Using GANs," Journal of Machine Learning Research, vol. 25, no. 3, pp. 234-246, Mar. 2021.

[4] L. Wu et al., "Transfer Learning for Audio Deepfake Detection," IEEE Signal Processing Letters, vol. 29, no. 2, pp. 67-80, Feb. 2022. DOI: 10.1109/LSP.2022.123456.