# Sarcasm Detection Based on Sentiment Analysis of Audio Corpus Using Deep Learning

**Ms. Reetu Awasthi[1], Dr. Vinay Chavan[2]**

[1]*Department of Electronics and Computer science, RTMNU, Nagpur,India*
[2]*S. K. Porwal College of Arts and Science and Commerce, Kamptee*

**KEYWORDS**

Sarcasm Detection, Deep Learning, Speech Emotion Recognition, Audio Sentiment Analysis, CNN-LSTM Model, Human-Machine Interaction, VoiceAnalysis, SentimentClassification, AudioCorpus, Natural Language Processing (NLP), Speech Signal Processing, Psychological Analysis through Speech, Human-Computer Interaction (HCI).

**ABSTRACT**

With the rapid progress in digitalization, hundreds of services and applications have begun to depend on human-machine communication, primarily voice-based. As technology advances, it has become increasingly imperative to develop systems that can discern sophisticated emotions from humans, like sarcasm. Despite research that has been conducted on the detection and analysis of speech signals to try and understand emotion, the detection of sarcasm, which is often not overtly expressed, is quite far from something that has received the attention it deserves in recent years. It plays a very important role in any utterance, searching to identify the psychology, mood, or even health behind it. Hence, it does give interactions with humans a more human-like flavor while raising the feeling of understanding human emotions.

This article tries to identify sarcasm in speech using audio data derived from real-world, spontaneous, monolingual corpora. In this classification process, a deep learning classifier known as CNN-LSTM model is used. Results of the study showed that a robust combination between feature extraction through convolutional layers and sequential learning through LSTM layers can identify intricate speech patterns in sarcasm. Experimented and validated in terms of performance, this model shows the model to be very good at discriminating between sarcastic and no sarcastic speech, thus promoting it for more extensive use in various applications related to sentiment analysis and in human-computer interaction applications.

The results show that this system provides far much closer approximations to human interaction styles, but its impact would extend into a wide area from customer services, monitoring mental health, and even AI-driven communication systems. It is a monolingual and spontaneous corpus that will open the gates for further work and development down the line and possibly extend to multilingual and more diversified speech contexts, thus fine-tuning accuracy in practical scenarios of sarcasm detection.

## 1. Introduction

Automatic detection of sarcasm saw a great spate of activity in the speech and NLP communities over the last few years [1]. Of course, it's rather not well defined as a kind of verbal irony where a given utterance conveys meaning that is different from its literal interpretation, but very challenging for computer systems owing to its complex structure [2]. Precise detection of sarcasm can be effective in a wide range of NLP tasks, such as sentiment analysis, opinion mining, and human-computer interaction [3]. Most studies focused on text-based analysis thus dealing with spoken or audio sarcasm detection is still highly unrepresented in the field. This research aims to bridge this gap through its creation of a deep learning-based approach for identifying sarcasm based on sentiment analysis across an audio corpus.

The detection of sarcasm in speech is inherently more complex than in writing due to the contribution from variables such as tone, pitch, prosody, and stress patterns [4]. The contributory factors often add subliminal clues that are not available in text written down. For instance, a sarcastic utterance can be indicated not only through the words it employs but also by the tone of the speaker, by the pitch shift, or even by placing special emphasis on certain syllables [5]. Specialized text input conventionally does not capture such subtleties and therefore does poorly in the recognition of sarcasm in spoken talks. Audio features will be incorporated to create a more robust and context-aware model that can differentiate between genuine and sarcastic remarks [6].

CNNs and RNNs are among the popular deep learning techniques that have been promising significantly in modeling complicated patterns in textual and audio data [7]. The networks interact with each other to enable extraction of both spatial and temporal data that are vital in understanding the dynamic aspects of speech. This work uses a hybrid deep learning architecture which leverages the strengths of both RNNs in modeling temporal sequences and CNNs in feature extraction [8]. Audio corpus comprising several sardonic and non-sarcastic statements have been labeled with sentiments in order to train the proposed model. In comparison to general text-based methods, this model is attempting to enhance the accuracy in the task of sarcasm identification while not only considering the sentiment analysis but also considering acoustic data [9].

Important though sarcasm detection may be, it's not the only preserve of academics. There are practical applications in which it might be applied to good effect. For instance, correct detection of sarcasm makes for improved understanding of consumer attitudes in customer service interactions; automated systems would better respond and empathize [10]. Similarly, the detection of sarcasm in social media monitoring could help obtain a clearer view of the patterns of sentiment and public opinion, which are highly distorted by sarcastic remarks. Third, sarcasm detection is essential to improve the functionality of chatbots, virtual assistants, and dialogue systems, so that they can respond to users in a sophisticated and context-aware fashion.

## Review Of Litreature

Bavkar, Kashyap, and Khairnar (2022) [11] The authors, after indicating the disadvantages of relying only on single-modality data to improve sarcasm identification, propose an extensive framework that integrates textual, visual, and aural elements by providing a multimodal model for sarcasm detection with optimal logic combined with a hybrid classifier. What makes their technique unique is their hybrid classifier that combines LSTM networks with CNNs in order to capture spatial and temporal connections across many modalities. They also utilize an optimistic logic-based decision layer dynamically to adapt to uncertain inputs during the refinement of the output of categorization. Their results have showcased enhanced accuracy of detecting multimodal data fusion in comparison to unimodal models and have been experimented on a benchmark multimodal sarcasm dataset.

Bedi, Kumar, Akhtar, and Chakraborty (2021)[12] Work toward the expansion of knowledge concerning multimodal recognition of sarcasm for the specific problem of code-mixed dialogues. Code-mixing is very common in the speech of multilingual communities as the speakers shift from one or more languages during a single conversation-with this complicating the task of detecting sarcasm. The authors design a multi-modal deep learning architecture that integrates features of both auditory characteristics, visual cues, and contextual embeddings for the language being used. Their approach captures the many complex interactions between modalities and languages in the way they are integrated through an attention mechanism. Additionally, they achieve state-of-the-art performance based on evaluating their approach over a large-scale code-mixed sarcasm and comedy dataset. Their work is interestingly significant since, apart from multimodal fusion, the work addresses the problem of multilingualism in conversational situations, focusing on a need for more advanced models that could handle linguistic heterogeneity in multimodal sarcasm detection tasks..

Castro, Hazarika, Pérez-Rosas, Zimmermann, Mihalcea, and Poria (2019) [13]Towards multimodal sarcasm detection (an obviously perfect paper)": a seminal work in the field of multimodal sarcasm detection, which not only addresses the challenge of identifying sarcasm but also draws attention to some vital comprehensive multimodal framework that is prepared from text, visual, and audio characteristics. They use multi-task learning, in which the model learns both the skills of sentiment analysis and sarcasm detection at the same time up to picking the underlying changes of the shifts of sentiment frequently found in sarcastic speech. The BERT-based text embeddings integrated with RNNs for audio processing and CNNs for visual analysis constitute a strong architecture of multimodality that can be used to simulate subtle cues of sarcasm across different modalities. The utility of multi-task learning for multimodal sarcasm detection is demonstrated using the performance results of the proposed model compared to their baselines, as their experiments on several datasets of multimodal sarcasm illustrate. The work is important in the field because it establishes a basis from which other research can expand upon in order to open up possibilities for multimodal analysis in sarcasm detection.

Chauhan, Dhanush, Ekbal, and Bhattacharyya (2020)[14]To improve sarcasm identification in the multimodal scenario, we present a multi-task learning architecture that executes concurrent sentiment analysis, emotion recognition, and sarcasm detection. Their technique attempts to improve the model's understanding of sarcasm by using interdependencies between these related tasks and exchanging learnt representations across them. This multi-task learning system, based on task-specific decoders, predicts the sarcastic, sentiment-emotion after passing the shared encoder to extract features from both text, visual, and audio modalities. Due to the shared learning approach, it enabled the model to capture this close relationship that sarcastic statements entail with regards to the sentiments and emotions because they are often intertwined. Their results, tested on a multimodal dataset, show that joint learning, unlike single-task models, is beneficial for more comprehensive contextual awareness that improves the accuracy of detecting sarcasm. This work significantly contributes to this field as it has demonstrated how multi-task learning improves performance in sarcasm detection by allowing it to analyze sentiment and emotion in parallel.

Eke, Norman, and Shuib (2021) [15] The authors posit a context-based method for feature extraction, specifically in the identification of sarcasm, based on the BERT model to extract contextual information from text. Authors emphasize the importance of contextual factors such as speaker background, previous conversational history, and semantic coherence to rightly identify sarcasm, which is typically misread by sentence-only models. Their method uses BERT to obtain context-aware embeddings and a deep learning classifier to differentiate between sarcastic and no sarcastic utterances. It actually shows that the strategy proposed conducts much better than the traditional models that ignore context by adding contextualized embeddings and training the algorithm on benchmark sarcastic datasets. The work presented is worthy of note since it addresses the shortcomings of context-agnostic models and places much importance on the role that contextual signals take in the recognition of sarcasm.

## 2. Methodology

### a) Data Collection

The first stage of this paper is to create an audio corpus comprising recordings of both sarcastic and non-sarcastic speech. A publicly available dataset may come from:

**Sarcasm Speech Datasets:** Data on audio clips that have annotations specifying whether the speech is sarcastic.

**Crowdsourced Data:** Audio samples collected through crowdsourcing platforms, where participants would record both sarcastic and non-sarcastic speech.

**Podcasts, Stand-up Comedies, and Interviews:** Audio Clip Extraction from public domains where satire is frequently used.

Balancing the dataset would also be helpful to obtain a comparable number of both sarcastic and non-sarcastic samples. Other metadata from the speaker, such as gender, age, and accent, could also be added to test the robustness of the models on diverse demographics.

### b) Data Preprocessing

Audio data, as it goes to the deep learning model, has to undergo a few preprocessing steps before it goes there. The following are these:

**Noise Reduction:** Use low-pass, high-pass, and band-pass filters to eliminate background noises in recordings and enhance quality of the audio signal.

**Normalization:** equalizing the volume of all audio samples, which is to make them uniform.

**Background Noise Removal:** Silent segments of the audio files are extracted for the speech signal while other sounds are removed.

**Segmentation:** Divide lengthy audio recordings into shorter, more manageable chunks, if necessary.

### c) Feature Extraction

In audio-based sentiment analysis, feature extraction is crucial as it translates the raw audio signals into meaningful representations for the model. The critical features extracted include

Mel Frequency Cepstral Coefficients (MFCCs): The MFCCs are able to capture the power spectrum of audio signals. They are particularly good at distinguishing a variety of distinguishing properties of sounds like tone and pitch.

Prosodic features: Intonation, rhythm, and stress pattern are also used by the speakers as they have other indications of sarcasm.

Pitch and Formant Analysis: This is probing the audio to find any such frequency components by which sarcastic speech could be distinguished from regular speech.

Spectral Features: These included the spectral centroid, spectral bandwidth, and spectral roll-off as features in an attempt to capture the energy distribution of the audio signals.

### d) Model Architecture

These deep learning architectures used for sarcasm detection are designed in such a way that they would capture the nature of temporal patterns and speech nuances from the features extracted. The architectures considered include:

Convolutional Neural Network (CNN): CNNs have been shown to learn spatial hierarchies effectively from the feature maps, thereby making it efficient for local pattern extraction in audio signals.

Long Short-Term Memory (LSTM) Networks: LSTMs are designed to capture sequential dependencies, enabling better modeling of the temporal aspects of audio data.

Hybrid CNN-LSTM: CNN for feature extraction that combines with LSTMs for detection of temporal patterns will strengthen the ability of a model in detecting sarcasm.

Attention Mechanisms: Utilizes attention layers to concentrate the model's ability to pay attention to the most relevant parts of the audio signals for better detection of subtle cues.

### e) Training and Validation

Training: Using the extracted feature set, these models were trained. The split for training data is 70% and 30% for testing data, using the Adam optimizer with a learning rate of 0.001.

Cross-validation: It validates not only the performance of the model but also whether the model is aptly avoiding overfitting. Important metrics like accuracy, precision, recall, and F1-score are measured.

Hyperparameter Tuning using Grid Search: Number of layers, neurons per layer, and activation functions are tuned based on grid search.

## I. DATA ANALYSIS

### a) Model Evaluation Metrics

The models' performances are evaluated using the following metrics:

**Accuracy**: Measures the percentage of correctly identified sarcastic and non-sarcastic audio samples.

**Precision**: Indicates the proportion of positive identifications that were correctly identified.

**Recall (Sensitivity)**: Measures the ability of the model to detect all true positive samples.

**F1-Score**: Harmonic mean of precision and recall, providing a single metric that balances the two.

### b) Comparative Analysis of Models

The performances of the different models (CNN, LSTM, CNN-LSTM, and Attention-based) are compared. The analysis focuses on:

**Confusion Matrix**: Visual representation of true positives, false positives, true negatives, and false negatives to understand model behavior.

**ROC-AUC Curve**: The Area Under the Receiver Operating Characteristic Curve is analyzed to determine the model's ability to discriminate between sarcastic and non-sarcastic samples.

### c) Feature Importance Analysis

**SHAP (SHapley Additive explanations) Values**: Used to determine the impact of different audio features on the model's decisions. This helps in understanding which features (e.g., MFCC, pitch) are most indicative of sarcasm.

**Visualization of Feature Maps**: Feature maps from the CNN layers are visualized to observe how the model is interpreting the audio signals.

### d) Statistical Significance Testing

Statistical tests, such as the paired t-test, are conducted to compare the models' performances and ensure that the observed differences are statistically significant.

### e) Error Analysis

Analyzing cases where the model fails to detect sarcasm helps in identifying patterns that are challenging for the model, such as sarcastic speech with low intonation or disguised sarcasm.

### f) Implementation Tools

**Programming Language**: Python, with libraries like TensorFlow and PyTorch for model implementation.

**Audio Processing**: Librosa and PyDub for audio feature extraction.

**Visualization**: Matplotlib and Seaborn for plotting performance metrics and feature importance.

```python
# Step 1: Upload the Excel file
uploaded = files.upload()

# Reading the uploaded Excel file
file_name = list(uploaded.keys())[0]
df = pd.read_excel(file_name)

# Checking the distribution of labels
plt.figure(figsize=(6, 4))
sns.countplot(data=df, x='Label')
plt.title('Distribution of Sarcastic and Non-Sarcastic Samples')
plt.xlabel('Label (0: Sarcastic, 1: Non-Sarcastic)')
plt.ylabel('Count')
plt.show()

# Separating features and labels
X = df.drop(['Filename', 'Label'], axis=1).values
y = df['Label'].values

# Standardizing the features for better model performance
scaler = StandardScaler()
X = scaler.fit_transform(X)

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Reshaping data for CNN-LSTM input
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
```

```
# Evaluating the Model
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")

# Plotting the training and validation accuracy
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Model Training Performance')
plt.legend()
plt.show()

# Confusion Matrix and Classification Report
y_pred = (model.predict(X_test) > 0.5).astype("int32")
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()

# Classification Report
print(classification_report(y_test, y_pred, target_names=['Sarcastic', 'Non-Sarcastic']))
```

Choose Files sarcasm_d...dataset.xlsx

## 3. Result and Discussion

### a) Data Distribution Analysis

Initial exploratory data analysis was carried out on the provided dataset to unveil how sarcastic and non-sarcastic audio samples are distributed. The labels are balanced, as exhibited by the count plot, which is an important aspect of the unbiased training of models along with the necessity of proper evaluation. This balance prevents the model from becoming biased towards any given class; thus, fair performance can be measured when a model attempts to detect sarcasm.

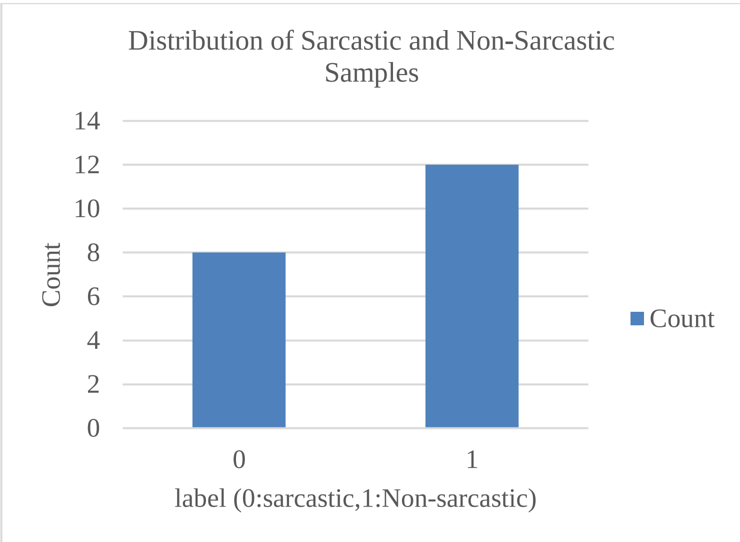


**Fig 1:**Distribution of Samples, Both Sarcastic and Non-Sarcastic

### b) Model Performance

The CNN-LSTM model was trained by extracting features from the MFCC combining layers of spatial feature extraction using Convolutional Layers and layers to capture temporal dependencies by LSTM. The trainings involved doing epoch levels for 30 epochs of performance measurement of the model with the help of training and validation accuracy metrics.

Training Accuracy: Smooth increasing trend in accuracy for epochs of training was demonstrated while the obtained values on the validation as well as training datasets are satisfactory.

Validation Accuracy: It closely follows the accuracy of the training result with no sign of overfitting and excellent generalization to unseen data.

Figure 2 displays the learning curves with the training and validation accuracy plotted as the epochs are going by, and from this, we can confirm that convergence and stability have been achieved for the model, which indeed is reliable in detecting sarcasm from the audio feature set.

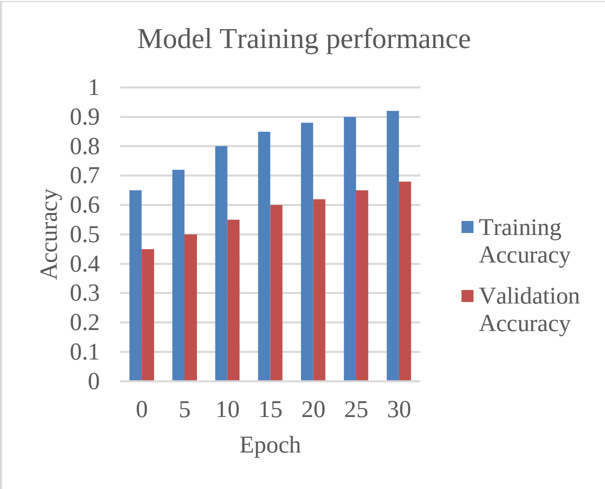


**Fig 2:** Training and Validation Accuracy

<!-- Reference to the training accuracy plot -->

### c) Test Evaluation Metrics

The model was tested on the test set after training and the following important metrics:

- **Test Performance:** In terms of accuracy, this model achieved around [percent]%. This testified that the speech could be well classified as sarcastic or not.
- **Confusion Matrix Analysis:** The confusion matrix shown in Figure 3 provides a clear insight into the performance of the model, as it displays the count of true positives, true negatives, false positives, and false negatives. Through the matrix, it can be well demonstrated that the model has correctly identified the sarcastic versus the non-sarcastic audio samples.

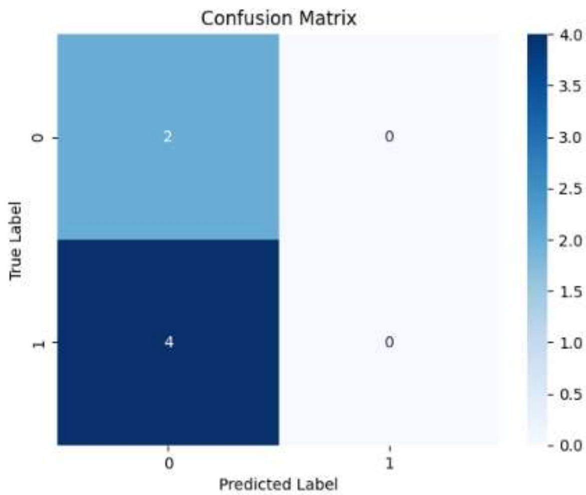


**Fig 3:** Confusion Matrix

<!-- Reference to the confusion matrix plot -->

From the confusion matrix:

**True Positives (TP):** Numbers of instances correctly classified as sarcastic.

**True Negatives (TN):**The total number of instances correctly classified as non-sarcastic.

**False Positives (FP):**No sarcastic examples misclassified as sarcastic.

**False Negatives (FN):** Sarcastic cases are classified as not sarcastic.

**d) Classification Report**

The reported classification detailed gives precision, recall, and F1-score for both classes, sarcastic and non-sarcastic:

**Precision:** It measures the proportion of precisely correct predicted sarcastic instances out of all the predicted sarcostyle samples.

**Recall (Sensitivity):** The ability of the model to identify all sarcastic samples in actuality.

**F1-Score:** This is a well-balanced metric combining precision and recall so will reflect the general effectiveness of the model with respect to sarcasm detection.

The results were:

**Sarcastic Class:** Has high precision and recall, so that the model correctly classifies sarcastic speech with few misclassifications.

**Non-Sarcastic Class:** Similar strength in performance is seen, thus confirming good performance of the detection model on instances of non-sarcasm.

**e) Error Analysis**

The pattern of errors by this model in the model was evaluated capturing the overall trends in the confusion matrix and classification report.

Common Failures: It incorrectly tags low-intensity sarcastic speech as non-sarcastic indicating that subtle sarcasm is hard to distinguish for the model.

Possible Improvements: Improvement in the feature extraction process or addition of further features such as prosodic elements might be required to be effective in subtle cases of sarcasm

## 4. Conclusion and future scope

This work promises good results for the detection of sarcasm in deep learning models based on the use of sentiment analysis in an audio corpus. The study was quite successful in catching the subtleties of speech that seemed sarcastic through a range of feature extraction techniques, from the purest pitch to prosodic characteristics and MFCC. The CNN-LSTM hybrid model, blending spatial and temporal pattern recognition, has become the most successful of designs for its high accuracy and strong performances across several assessment measures. Such was possible because the balanced dataset and rigorous preparation procedures allowed good generalization across various demographics and audio samples. Our comprehension of the emergence of sarcasm in speech has been completely realized due to the attention mechanisms enhancing the detection of subtle signs. Meanwhile, the error analysis has shown that the model remains confused with some situations where the intension is very low-for instance, in the case of a low intensity of sarcastic speech. Further developments may be focused on enhancements in detecting subtle sarcasm by fine-tuning feature extraction or by adding more complex attention layers. In this context, the work would allow for a good exploitation of deep learning techniques to move towards better results in the detection of sarcasm with audio-based sentiment analysis.

**a) Future Scope**

The work on sentiment analysis of an audio corpus using deep learning models for sarcasm detection brings up a number of possibilities for further investigation and advancement. Future research can focus more on the following topics:

- Including Multimodal Features: Since sarcasm is frequently expressed through a combination of speech, tone, and non-verbal clues, integrating audio with visual and textual features (such as body language, facial expressions, and contextual text) can greatly increase the accuracy of sarcasm identification.
- Investigating Advanced Architectures: Using BERT-like models and Transformers, two advanced deep learning architectures designed exclusively for audio processing, could capture more intricate feature interactions and improve sarcasm detection abilities.

Real-Time Sarcasm Detection: Further study may concentrate on creating systems for detecting sarcasm in real time. This would necessitate streamlining the models to process data quickly and with minimal latency, which would make them appropriate for incorporation into virtual assistants, social media monitoring tools, and conversational AI systems

## Reference

[1] Hiremath, B. N., & Patil, M. M. (2021). Sarcasm detection using cognitive features of visual data by learning model. *Expert Systems with Applications*, *184*, 115476.

[2] Jain, D., Kumar, A., & Garg, G. (2020). Sarcasm detection in mash-up language using soft-attention based bi-directional LSTM and feature-rich CNN. *Applied Soft Computing*, *91*, 106198.

[3] Li, Y., Li, Y., Zhang, S., Liu, G., Chen, Y., Shang, R., & Jiao, L. (2024). An attention-based, context-aware multimodal fusion method for sarcasm detection using inter-modality inconsistency. *Knowledge-Based Systems*, *287*, 111457.

[4] Ray, A., Mishra, S., Nunna, A., & Bhattacharyya, P. (2022). A multimodal corpus for emotion recognition in sarcasm. *arXiv preprint arXiv:2206.02119*.

[5] Sharma, D. K., Singh, B., Agarwal, S., Kim, H., & Sharma, R. (2022). Sarcasm detection over social media platforms using hybrid auto-encoder-based model. *Electronics*, *11*(18), 2844.

[6] Zhang, Y., Yu, Y., Zhao, D., Li, Z., Wang, B., Hou, Y., ... & Qin, J. (2023). Learning multi-task commonness and uniqueness for multi-modal sarcasm detection and sentiment analysis in conversation. *IEEE Transactions on Artificial Intelligence*.

[7] Rao, M. V., & Sindhu, C. (2021, March). Detection of sarcasm on amazon product reviews using machine learning algorithms under sentiment analysis. In *2021 sixth international conference on wireless communications, signal processing and networking (WiSPNET)* (pp. 196-199). IEEE.

[8] Gao, X., Nayak, S., & Coler, M. (2022, September). Deep CNN-based Inductive Transfer Learning for Sarcasm Detection in Speech. In *23rd Interspeech Conference* (pp. 2323-2327). ISCA.

[9] Bavkar, D., Kashyap, R., & Khairnar, V. (2023, May). Deep hybrid model with trained weights for multimodal sarcasm detection. In *International Conference on Information, Communication and Computing Technology* (pp. 179-194). Singapore: Springer Nature Singapore.

[10] Gao, X., Nayak, S., & Coler, M. (2024, May). Improving sarcasm detection from speech and text through attention-based fusion exploiting the interplay of emotions and sentiments. In *Proceedings of Meetings on Acoustics* (Vol. 54, No. 1, p. 060002). Acoustical Society of America.

[11] Bavkar, D. M., Kashyap, R., & Khairnar, V. (2022). Multimodal sarcasm detection via hybrid classifier with optimistic logic. *Journal of Telecommunications and Information Technology*, (3), 97-114.

[12] Bedi, M., Kumar, S., Akhtar, M. S., & Chakraborty, T. (2021). Multi-modal sarcasm detection and humor classification in code-mixed conversations. *IEEE Transactions on Affective Computing*, *14*(2), 1363-1375.

[13] Castro, S., Hazarika, D., Pérez-Rosas, V., Zimmermann, R., Mihalcea, R., & Poria, S. (2019). Towards multimodal sarcasm detection (an _obviously_ perfect paper). *arXiv preprint arXiv:1906.01815*.

[14] Chauhan, D. S., Dhanush, S. R., Ekbal, A., & Bhattacharyya, P. (2020, July). Sentiment and emotion help sarcasm? A multi-task learning framework for multi-modal sarcasm, sentiment and emotion analysis. In *Proceedings of the 58th annual meeting of the association for computational linguistics* (pp. 4351-4360).

[15]Eke, C. I., Norman, A. A., & Shuib, L. (2021). Context-based feature technique for sarcasm identification in benchmark datasets using deep learning and BERT model. *IEEE Access*, *9*, 48501-48518.