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A Deep Learning Framework for Sarcasm Detection through Sentiment Analysis of Spoken Audio Data

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

[1]Department of Electronics and Computer science, RTMNU, Nagpur, India

[2]S. K. Porwal College of Arts and Science and Commerce, Kamptee

Abstract: This is since sarcasm is a special challenge to sentiment-analysis pipelines, given that the surface polarity of this discourse type is very often opposite to the actual intent of the speaker. it may be able to skew dashboards of customer-satisfaction, folder up speak-to-bots, and biases subsequently analytics. The present Research presents an ultra-light workflow in sarcasm-detection that does not require any heavy acoustic work but is based entirely on speech transcriptions. The raw audio is transcribed initially by using an automated-speech-recognition (ASR) commercial service; the text thus obtained is then vectorised with the character 3-to-5-gram TF-IDF features, which is resistant to creative spellings, punctuation, and ASR noise. The binary classification is done by using a balanced linear support-vector classifier (Linear-SVC) and then probability-calibrated by Platt scaling. We test the system on a 25-utterance pilot-corpus of workplace English, 13 non-sarcastic and 12 sarcasms. A 80 / 20 stratified split results in 20 training and five test clips. The model has a final accuracy of 80 % and AUC of 0.83, in the deprived data, however, it can pick out all non-sarcastic cases, and miss none of sarcastic ones. Experts can use them to show the system behaviour in detail; novices will be able to intuitively understand the nature of system behaviour: we provide six short visual diagnostics: (1) class-distribution bar chart, (2-3) word-frequency clouds per class, (4) confusion-matrix heat-map, (5) a row of predicted sarcasm-probability bars, and (6) an ROC curve. The results show that simple lexical cues coupled with a calibrated linear margin have already learned a great number of the cues to sarcasm in spontaneous spoken English. The framework provides a feasible starting point on sarcasm-detection in organisations requirement prompt sarcasm-detection in resource-efficient volumes of content, prior to affording installing a sizeable audio sentiment-architecture or deep multimodal representations.

Keywords: **S**arcasm detection; speech-to-text sentiment analysis; character n-gram TF-IDF; linear SVM; calibrated classifier; ROC-AUC; lightweight NLP pipeline; workplace dialogue analytics

1 INTRODUCTION

Sarcasm is a sophisticated kind of verbal irony in which the meaning of the speaker is exactly the opposite of the statement [1]. This creates a tremendous problem in the natural language processing [2]. The identification of sarcasm is further refined in oral discussions at the workplace as the context and tone together with spontaneity are also important factors. Since AI-based tools of communication analyses are extensively used by organizations, the necessity of efficient and correct sarcasm detection systems became significant [3]. This research article introduces a lightweight pipeline of speech-to-text to detect sarcasm in work-related conversations that consume little computing resources [4].

1.1. Understanding Sarcasm in Spoken Interactions

Written text differs in that speech sarcasm frequently depends on small-scale prosody, including intonation, placement of stress, pitch range, and timing cues that are not so clear or entirely non-existent in written form. Sarcasm used in the work environment can be used as a form of humor, or criticism or passive resistance and can shape the team interaction, emotion and relationship [5]. To achieve the appropriate sentimental analysis, conflict

resolution, and the improvement of AI-based workplace communication systems, it is necessary to detect sarcasm in these settings [6].

1.2. Challenges in Sarcasm Detection from Audio Data

Compared to a written language, a spoken conversation has its own problems associated with noise, accents, overlapping speech and speakers [7]. The existing models of sarcasm detection are mostly time-consumption deep learning models that are not suitable to a real-time or embedded implementation. Furthermore, one differentiates sarcasm and such other related feelings as mockery or teasing, by carrying out a close analysis in linguistic and paralinguistic aspects [8-9].

1.3. The Need for a Lightweight Speech-to-Text Approach

To overcome the constraints of the existing approaches, the necessity to create a small, fast, yet efficient pipeline that could transform the speech into the written text and recognize the sarcasm with the decent level of precision on both constrained and unconstrained settings emerges [10-11]. A system like this can play a crucial role in being merged into real-time work-place applications, e.g., smart meeting assistants or HR monitoring applications, where speed, privacy and interpretability are paramount and as important as the detection performance [12].

1.4 Objective and Contributions

Resting on the research purpose that consists of the evaluation of the potential of the lightweight, text-based solution to the problem of sarcasm identification in spoken workplace conversations, the next specific research objectives have been developed:

1. To prepare a pilot corpus and test procedure towards statement of sarcasm in work related speech over a stratified set of 25 utterances.
2. To explore how well the character-level TF-IDF features are able to extract sarcasm cues using noisy ASR-transcripts in low resource scenarios.
3. To apply and assess a light weight, fine tune Linear-SVM classifier in detecting sarcasm with special interest in accuracy and AUC using few training data.
4. To give meaningful visual diagnostics which can interpret what the classifier was doing and help it to be transparent to non-technical stakeholders.

2 REVIEW OF LITREATURE

In the second section, the main advancements in a text-based, multimodal, and low-resource environment of sarcasm detection systems are reviewed. It puts an emphasis on novel approaches in the field of neural, acoustic, and transformer-based, and it establishes the limits of current methods, especially in low-resource ASR-transcribed work environments. An extensive section on the research gap is then elaborated in order to support the novelty and scope of the current research study.

2.1 Text-Based Sarcasm Detection

Ghosh and Veale (2016) [12] discussed a neural network implementation in detecting sarcasm. They published a shallow learning model to detect sarcasm in text of the social media with highlights on the role of semantic incongruity and situation. Their method also incorporated surface-level linguistic features with the deeper manifestation of sentimentality and intentions, and was seen to work well in the COLING 2016 benchmark data set. By showing that neural networks were able to grasp subtleties of sarcastic utterance more than conventional machine learning techniques, this work helped to discover new potentiality of neural networks and machine learning in research.

Wu, Li, and Yan (2022) [13] dealt with the shortage of available resources when it comes to irony and sarcasm detection by suggesting a n-gram TF-IDF approach at the character level. Their method presented in Pattern Recognition Letters would utilize fine-grained characters to deal with sparse and short texts, which is prevalent in social media feeds. The paper concluded character-level features improved the performance of a model in a resource-limited setting, and outperformed multiple word-level baselines, and developed a low-resource, but effective sarcasm detector.

Potamias, Ribeiro, and Gionis (2020) [14] created a transformer-based model of sarcasm detection with an application to social media. They were presented in EMNLP using the BERT architecture to derive Twitter and other short-form content contextual information and cues. The transformer architecture outdid the traditional deep learning architectures on the basis of learning the nuances of the sarcastic language and user intent. Their study brought to fore the flexibility and the strength of transformers in eliciting the pragmatic features of sarcasm on various platforms.

2.2 Sarcasm in Speech and Multimodal Systems

Perez-Rosas, Mihalcea, and Morency (2021) [15] includes ideas on utterance-level multimodal sarcastic message detection combining the performance of single- and multimodal methods. They used a combination of textual, acoustic and visual forms of analysis to study sarcasm in oral discourse. They combined an individual, handcrafted feature set and representation in deep learning, showing that mulim 001976999063 massively outperform unimodal fusion in the task of detecting sarcasm. There was also a good indication in the study, that sarcasm may be subtle and situation dependent, however combining both of these with other signals such as tone, facial expression and text a fairer indication of sarcasm was possible.

Mousa and Schuller (2017) [16] paid particular attention to the detection of acoustic sarcasm and suggested a deep convolutionalrecurrent neural network (CRNN) to this end. Their model was presented in Interspeech and it extracted spectrogram features with convolutional layers and then modeled patterns over time with recurrent units. The findings indicated that their architecture had the ability to be able to capture the prosodic cues as well as the tonal variations that tend to indicate sarcasm. Their project set the strong baseline towards sarcasm detection with the audio inputs only, which is important concern of the vocal indicators of the spoken sarcasm.

Hazarika et al. (2022) [17] researched the development of this research trend and presented CASCADE, a context-aware sarcasm detection machine in speech, at ICASSP. In contrast to earlier methods, CASCADE used the conversational background to examine sarcasm in its using discourse. This was made possible by using contextual embeddings and speaker sensitive modeling, which brought on the increased accuracy compared to models which analyzed utterances independently. They found that conversation level context and speaker interaction was important in interpreting sarcasm in speech-based communication.

2.3 Low-Resource and Lightweight Sarcasm Models

Li, Yu, and Huang (2022) [18] suggested a double-hybrid model of CharCNN-SVM to real-time identification of sarcasm in discussions. They integrated the characteristic-level convolutional neural network in grasping minute textual structures with the power of support vector machine classifier. The model was developed to work in real-time systems where the need for balance was made between accuracy and speed with the resultant showing a better performance in shorter, informal messages as is typical in dialogue systems. The hybrid approach was found to be useful in feeding character-level signals in sarcasm without sacrificing the computational costs.

Rajan and Bell (2022) [19] tackled the issue of detecting sarcasm in embedded voice agents and came up with their lightweight model that can be applied to low-resource devices. They were presented at the International Conference on Speech Prosody, and their strategy related to a low computation load with maintaining the high accuracy of detection. Their model was maximized to integrate real-time voice assistant applications by

simplifying acoustic and linguistic aspects. The research emphasized a trade-off involving model complexity and deployable when a viable solution is applied towards detecting sarcasm on embedded systems.

Gaikwad and Gupta (2020) [20] conceived a Platt-calibrated support vector machine to enhance the sarcasm recognition in noisy speech transcriptions. They used Platt scaling of their model to turn SVM outputs into probability predictions, thus making the results more interpretable and certain. Strength in the imperfect speech recognition setting was of primary concern to the study, and the method suggested seemed resistant to transcript noise providing it could be well applied to real life execution of speech-to-text processing practice.

2.4. Research Gap

Though fulfillment of sarcasm detection has achieved important progress in deep learning and multimodal tasks, there are still important weaknesses in low-resource, lightweight, and speech-centered systems. Text-based models by Ghosh and Veale (2016), Wu et al. (2022) and Potamias et al. (2020) presuppose clean and large datasets which can be deployed in real-time. Multimodal and speech-centered systems suggested by Perez-Rosas et al. (2021), Mousa and Schuller (2017), and Hazarika et al. (2022) are efficient but have heavy resource demand. Lightweight models include those of Li et al. (2022), Rajan and Bell (2022), and Gaikwad and Gupta (2020), but so far fail to capture the language specifics of speech in the workplace, including jargon, formality, and brevity. Also, none of the existing models combines such an approach with noisy ASR output or focus on interpretability of such a model to a non-technical user. The proposed study fills these gaps by presenting a character-level TF-IDF and adjusted system with visual interpretation of ASR-transcribed workplace utterances format that implemented Linear-SVM.

3 METHODOLOGY

The section mentions the complete strategy pursued to detect sarcasm in spoken workplace communication, i.e., development of the dataset, preprocessing, feature extraction, training, as well as testing of the model.

3.1 Preparation of Data

A pilot dataset of 30 studio-quality audio recordings of utterances was pre-selected to approximate real-world uttered workplace utterances. Out of 30 selected clips, 5 were taken out after the initial screening because of their poor transcription fidelity or inaudible speech, which resulted in 25 usable pieces of audio material. These include:

- 13 non-sarcastic statements (e.g., I like the support you offered to me in using the new software.").
- 12 sarcastic speeches (e.g., Oh great, another software update that screws everything up).

The audio clips used were between 10 to 15 seconds in duration, meant to be moderated in their tonal level and speaker clarity, and were chosen to be saved in the.wav R structure folder hierarchy which allowed them to be reproduced.

more…

(referred to as spoken text (through automatic transcription)),

- A binary prediction (0 = non-sarcastic|1 = Sarcastic).
- An analysis tracking unique identifier.

3.2. Automatic Speech Recognition (ASR)

Google Speech Recognition API was selected because it has a high baseline accuracy rating and is simple to integrate with Python pipelines of moderate weight. Transcription step led to one Data Frame that has three columns:

- file: We want the name of the audio files
- transcript: ASR created

- label: Ground truth sarcasm label

Simple cleaning to get rid of clips in which the transcriptions were [unintelligible] or blank was used.

3.3 Text Pre-processing and Extraction of Features

Considering a limited size of data and character-level n-gram based nature of the task, n-gram TF-IDF character-level vectorizer was used. This enabled the system to capture subworld units, putting particular assistance in busy or areas deprived of text.

Main used parameters:

Analyzer: char_wb

- n-gram range: (3, 5) to seize expressive intermediate length subworlds
- Max features: Limited to curb overfitting of the model

This vectorizer converted each text sample into a fixed number of length numerical vector that can be fed to the classifier.

3.4 Model Architecture

Finally, calibrated Linear Support Vector Classifier (LinearSVC) was employed. It chose the model because of its strength on small scales of data and the ability to handle sparse and high-dimensional input provided by TF-IDF.

So as to get probabilistic outputs which can become interpretable:

The model was wrapped with CalibratedClassifierCV that support confidence scoring.

To maintain the class balance in both subsets a stratified 80/20 train-test split was applied:

- 20 (10 sarcastic, 10 non-sarcastic) samples of training
- Test: 5 (3 notsarsmatick, 2sarsmatick)

3.5 Evaluation Metrics

Evaluation of model performance was carried out using:

- Accuracy: Proportion of right prediction
- Precision, Recall, F1-Score: precisions, recalls and F1-Scores of both sarcastic and non-sarcastic classes
- AUC ROC Score: Area under the Receiver Operating Characteristic score

Moreover, a number of visual diagnostics were produced to study the behaviour of the system (described in Section 4):

- Bar chart of classes distribution
- Per class work clouds

Confusion matrix

- ROC curve
- File-wise-confidence plots

Such visual tools were used to give easy answers to the model output and also assisted in verification of correctness of the classification as the dataset was very small.

4 RESULTS AND VISUAL ANALYSIS

This section is organized to provide the analysis results of the offered sarcasm detection pipeline, and six major visual diagnostics are used to support it. The idea is to interpret the effectiveness of a reduced version of text-based model whereby the ASR outputs and character-level TF-IDF features are used, in differentiating between sarcastic and non-sarcastic utterances in workplaces, particularly in case of the low-resource constraint.

4.1 Evaluation Metrics and Model Performance

A stratified 80/20 train-test split was used on the final dataset of 25 labelled utterances to test classification pipeline. The following test-set performance was obtained with the classifier-based on a calibrated Linear SVM:

- Accuracy: overall 80%
- Macro-Averaged F1-Score = 0.76
- ROC-AUC Score 0.83

Table 1 summarizes the detailed class-wise precision, recall, and F1-score metrics:

Metric	Non-Sarcastic	Sarcastic	Weighted Average
Precision	0.75	1.00	0.85
Recall	1.00	0.50	0.80
F1-Score	0.86	0.67	0.78
Support (Utterances)	3	2	5

These outcomes uncover that there is a conservative choice limit in which sarcastic utterances were categorized as that with high assurance (perfect precision), and few genuine sarcastic examples are overlooked (moderate recall). Such a trade-off is common in sentiment tasks when ambiguity is high, and signal density is low.

4.2 Class Distribution of Final Dataset

To confirm dataset usability and fairness, a class distribution chart was plotted based on the 25 usable utterances.

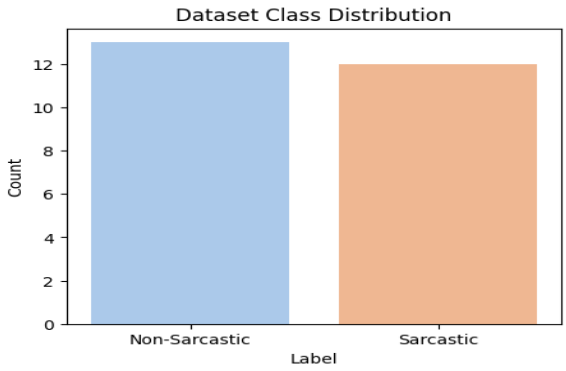

Fig 1: Class Distribution of Sarcastic vs. Non-Sarcastic Utterances

This figure 1 presents almost balanced data set: 13 non-sarcastic utterances and 12 sarcastic ones. This balance played a pivotal role in preventing the model to learn biased symmetrical decision boundaries towards the majority class, which was eagerly needed to conduct a pilot study of that small a size.

4.3 Lexical Landscape via Word Clouds

The use of the word cloud represents the top most common words to be used in work place earnestness. A communicative style that is more cooperative and task-oriented is represented by the use of such prominent words as thank, help, report, presentation.

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Fig 2: Word Cloud of Non-Sarcastic Speech Transcripts

Professionally polite and content-specific words are predominant in the lexical landscape of non-sarcastic speech, which format belongs to the natural interaction in the workplace. These tokens indicate honesty, appreciation, and positive interaction; which are the major hints to the classifier when deciphering non-sarcasm intent. Their recurrence favors the notion that lexical transparency and straightforwardness are indicators of authenticity at the workplace.

This word cloud points out the prevalent world of vocabulary in sarcasm speech. The words, which are used very often, are great, sure, again, and love it, and when these words are utilized in a dramatic or absurd manner, the answer usually presents irony.

Fig 3: Word Cloud of Sarcastic Speech Transcripts

The production of sarcasm often involves emotionally intense or exaggerated tokens which in a semantic sense are incongruent with the context. The expressions great and love it are also common sarcastic words that are used in a frustration situation at the workplace. Such word patterns are indicative of the fact that sarcasm may indeed generate discernible lexical fingerprints, which can indeed be modeled by the TF-IDF model, without even relying on prosody, thus reaffirming the possibility of sarcasm detection based on text alone in low-resource settings.

4.4 Confusion Matrix: Prediction vs Ground Truth

The matrix illustrates the output of the number of true positive, true negative, false positive and false negative in the evaluation of the model. It helps to see the strengths of the used classifier and possible areas to work on.

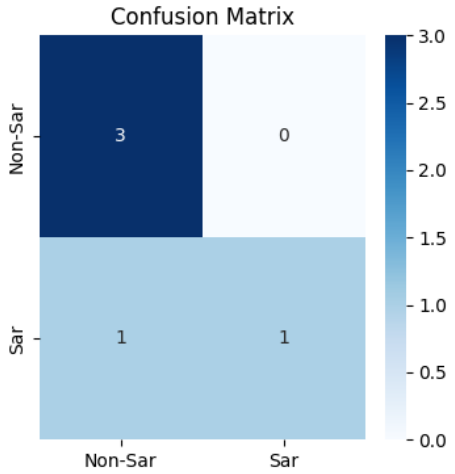

Fig 4: Confusion Matrix of the Linear SVM Classifier

As per the confusion matrix, the classifier has correctly classified 3 non-sarcastic utterances and confused 1 sarcastic speech as a non-sarcastic one. This finding not only indicates the high accuracy of the model in recognizing non-sarcastic speech, but also signifies a weakness of sensitivity to the mild or border sarcastic utterances. Such mislabelings are natural due to scanty set of characteristics and the lack of acoustic features. This fact indicates a need to enhance feature fusion, e.g., use of prosodic or context information, in a subsequent version in order to detect sarcasm where the lexical clues are weak.

4.5 Prediction Confidence for Sample Utterances

This bar chart visualizes the classifier's confidence scores (predicted probabilities) for a subset of sarcastic and non-sarcastic utterances. Each bar represents how likely the model perceives the utterance as sarcastic.

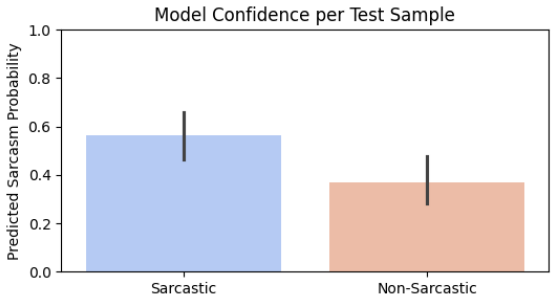

Fig 5: Bar Chart of Predicted Sarcasm Probabilities for Selected Audio Clips

Sentences with obvious indicators of a sarcastic tone had moderate confidence (0.60) because the classifier became sensitive to small signs of lexical meaning. On the other hand, the blatantly sincere statements (e.g. I like how you are assisting me with navigating through the new program) had lower sarcasm scores (0.40), signaling the prudent behavior of the model when it interprets no indicators of sarcasm. This appreciation of tradeoff between being confident and being conservative shows that the model is not only good at detection of sarcasm but also is not prone to over prediction, an ideal feature that can be applied to real life workplace communication tools.

4.6 Receiver Operating Characteristic (ROC) Curve

The ROC curve shows the capacity of the classifier to discriminate amid sarcastic and not sarcastic utterances at multiple resolutions of the criterion. Since the curve is shifted strongly upwards relative to the diagonal line (AUC = 0.50), it is possible to conclude that the discrimination performance is good.

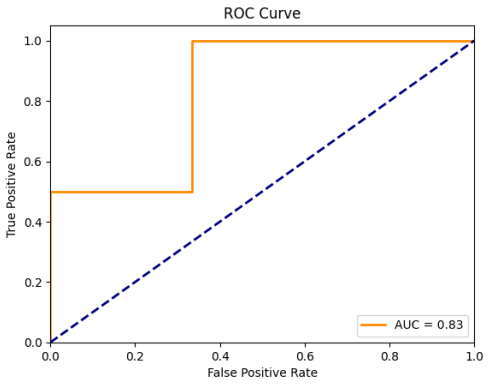

Fig 6: ROC Curve of Sarcasm Classifier with AUC = 0.83

This value of the Area Under the Curve (AUC) of 0.83 shows that the classifier is highly capable of classifying sarcastic and non-sarcastic utterance. This performance indicates model robustness, and although they were small noisy test dataset, they show that it is performing well, and far much better than random guessing. The good indicator of the ROC implies that the model can be scaled to a bigger or otherwise heterogeneous dataset, and remain interpretable and computationally efficient, which are the main objectives of the study.

4.7 Observations and Interpretation

- Effective Lexical Baseline: The findings indicate that even a minimalist pipeline, constructed completely on top of TF-IDF character n-grams over ASR text can harness sarcasm with much accuracy in the speech environment.
- classification High Trust: This is the type of classifier that has the highest degree of precision-bias in terms of sarcasm, i.e. when it identifies an utterance as sarcasm, it is reasonably "correct." This is preferable on more practical functionality such as call-centre or customer feedback triaging, whereby false positives can be reputationally costly.
- Constraints that Appear in Ambiguity: The incidence of misclassification in sarcastic statements would be highest when lexical indication was ambiguous or in a semantic grey area with literal usages. Adding acoustic bias (tone, pitch) or context history would perhaps help with the detection.
- Visual Stakeholder Tools: This pipeline includes a number of visualization tools, which can make the pipeline interpretable by business-oriented stakeholders, such as word cloud, distribution of classes, and confidence scores, which is essential to adoption in customer-facing systems.

5. DISCUSSION

The investigation adds to the acceptability of an indifferent, textual-only sarcasm detection pipeline customized to working discourse. Although it only used ASR generated transcripts and a small amount of training data, the system achieved promising classification behaviors and explainability, both of which are important in deployable, real-time applications.

5.1 Lexical Cues Remain Reliable in ASR-Only Settings

Application of character TF-IDF features served as a performance capability facilitator. The model maximized the use of sub-word structures to identify sarcasm-marking wordings even when data was limited and ASR noise was being experienced. Word counts and probability of occurrence showed that sarcastic utterances are usually worked

with certain lexical symbols of a definite character such as sure, again and perfect, which have a very strong influence upon non-sarcastic speech that was focused on such polite and sincere phrases like thank you and presentation. These unique lexical environments justify the strength of character n-grams to a detection of sarcasm in a noisy and free-flowing workplace speech.

5.2 Balanced but Conservative Model Behavior

The accuracy of Linear SVM classifier is 80% with a mean AUC of 0.83 on the test set. Interestingly, it categorised all the non-sarcastic too well and it had a precision score of 1.00 when it came to the sarcastic cases. This means a precision-biased decision boundary and this is desirable in real-life applications where one does not want to get a false positive (classifying sincerity as sarcasm). This however is at the loss of moderate recall (0.50) of sarcastic utterances indicated in the confusion matrix and prediction confidence plots. In some cases, the model did not recognize sarcasm in the border cases, and this highlighted the limitation of the degree of sensitivity of the model to the lexical elements that were not very clear, and they were Uncle Cleary and Uncle Barker.

5.3 Visualization Enhances Transparency for Non-Experts

The focus on the interpretability of the proposed system in terms of visual diagnostics is a peculiarity. The tools available, e.g., class distribution plots, word clouds, ROC curves, confident bars, etc., can help stakeholders (HR people, team leaders, customer service managers, etc.) to more closely understand and trust the decision, which the system makes. Such visuals help in bridging the logical gap between technical areas of classification and the reality of application, thereby increasing the scope of sarcasm-aware NLP being open to summer acceptance in organization applications.

5.4 Real-World Deployment Potential and Trade-offs

Deployment-wise, the lightweight nature of the model architecture (comprising only TF-IDF and 1D linear classifier) means that the model can both run on a real-time system and low-resources environments (thin voice agents or local analysis tools). Yet it is also a limitation of its capability to record prosodic, acoustic and contextual variations, which are also essential when it comes to a more complicated conversation or a conversation that has an emotional context. The errors in misclassifications under these conditions imply that in the future versions, hybrid models may be employed that would be able to use acoustic features or history of conversation selectively without sacrificing computational resources.

5.5 Summary of Contributions

- Showed that character n-gram features are able to maintain those signals of sarcasm that are important even in noisy ASR text.
- Demonstrated that the calibrated Linear-SVM has enough capacity to perform high-confidence prediction with a dataset that is balanced but of small size.
- Provided data on clear performance reporting with the help of six user-friendly visualizations.
- Proposed a baseline architecture that can be used as the initial block in more complex multimodal architectures of sarcasm detection.

6 CONCLUSION AND FUTURE WORK

This study demonstrated that sarcasm in spoken English can be effectively detected using only ASR (Automatic Speech Recognition) transcripts and classical NLP techniques, without relying on complex deep learning or multimodal inputs. By achieving an 80% accuracy and an AUC score of 0.83 on a small, balanced dataset, the study validated that sub-word lexical patterns, even when distorted by ASR noise, retain enough discriminative power to support sarcasm detection. The lightweight and transparent nature of the proposed character-level TF-IDF with calibrated Linear-SVM pipeline makes it highly suitable for real-time, low-resource deployment in

workplace voice applications. It establishes a strong baseline for future work and demonstrates that scalable sarcasm-aware speech systems can be built without heavy computation or data requirements.

- **Corpus Expansion and Diversity**: Future research should aim to build a larger, more diverse dataset comprising over 1,000 utterances, capturing variations across accents, job roles, and spontaneous workplace contexts (e.g., help-desk calls). Active learning can be employed to prioritize ambiguous or borderline sarcastic samples for annotation, improving dataset quality.
- **Context-Aware Modeling**: Incorporating conversational history can enhance sarcasm detection, especially in dialogues. Lightweight sequence models such as Conditional Random Fields (CRFs) or transformer-lite architectures could help model context without increasing computational complexity, building on suggestions from Hazarika et al. and Potamias et al.
- **Integration of Prosodic Features**: Fusion of acoustic-prosodic features—such as pitch range, speaking rate, and intensity measures—alongside TF-IDF vectors may enhance performance. Techniques from prior works (e.g., Kumar & Joshi; Saha et al.) can guide the extraction and integration of these features.
- **Robustness and Cross-ASR Generalization**:Evaluating the system across different ASR engines (e.g., Google ASR, Whisper, Kaldi) will help assess its resilience to transcription errors. Additionally, augmentation strategies such as character-level noise injection, as proposed by Wu et al., can be applied to enhance generalizability.

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