Sentiment Analysis of News from Security Perspective

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May 2024

Sentiment Analysis of News from Security Perspective

Major Project - I

Submitted in partial fulfillment of the requirements

for the degree of

Master of Technology in Computer Science and Engineering

Submitted By

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May 2024

CERTIFICATE

This is to Certify that the major project entitled "Sentiment analysis of news from a security perspective" submitted by Jainam Shah (22MCEC17), towards the partial fulfillment of the requirements for the degree of Master of Technology in Computer Science and Engineering With a specialization in Computer Science and Engineering of Nirma University is the record of work carried out by him my supervision and guidance. In my opinion, a submitted work reached level required for being accepted for examinations.

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STATEMENT OF ORIGINALITY

I, **Jainam Shah**, Roll. No. **22MCEC17**, give undertaking that the Major Project entitled "**Sentiment analysis of news from a security perspective**" submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Computer Science & Engineering** of Institute of Technology, Nirma University, Ahmedabad contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made. It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

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Signature of Student
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Place: Ahmedabad

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ACKNOWLEDGEMENTS

My sincerest thanks go to **Dr. Zunnun Narmawala** for his invaluable guidance and support throughout my study. His encouragement was crucial from start to finish, helping me grasp the complexities of the subject. I'm grateful to everyone who offered their support during this project. Special appreciation is also due to our college for supplying the necessary resources and materials. Your assistance has made all the difference.

I'm delighted to express my gratitude to **Dr. Madhuri Bhavsar**, Head of Computer Science and Engineering Department at Nirma University, for her generous assistance and for creating a nurturing research atmosphere.

We're grateful for the unwavering encouragement and support provided by **Dr. Himanshu Soni**, esteemed Director of the School of Technology at Nirma University, Ahmedabad. His guidance has been invaluable throughout this endeavor.

We're grateful to Nirma University in Ahmedabad, especially the Computer Engineering Department, for their invaluable guidance and thoughtful advice on our project work. Their dedicated support has been pivotal to our success.

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ABSTRACT

Illuminating Security Threats Hidden in News Sentiments. First, we analyzed sentiment analysis different approaches and method also which models are applicable and their performance, then to get good performance in sentiment analysis comments samples and a speech comprehensive dataset was collected and used for training and evaluating the models. Three different models were trained for comment sentiment analysis, namely Naive Bayes, Support Vector Classifier (SVC), and Long Short-Term Memory (LSTM) model. For comment sentiment analysis, the models were trained on a dataset consisting of labeled comments which we generated using VADER sentiment. The accuracy, recall, precision, and F1-score were used as evaluation metrics. The results showed that the LSTM model outperformed the Naive Bayes and SVC models in Performance metrics. For speech emotion recognition, the LSTM model was trained on a dataset consisting of labeled speech samples. The same evaluation measures were used as performance metrics. The results showed that the LSTM model achieved a final good Metrics suite. The results obtained suggest that the LSTM model is a promising approach for both tasks and could be further improved with additional data and optimization. To better capture the complexity of emotions, we're taking a multi-faceted approach in our research. We're not relying on words alone; instead, we're looking at how tone, pitch, and rhythm of speech, along with facial expressions and gestures, contribute to conveying feelings. By combining text, sound, and visual cues, our multi-modal sentiment analysis offers a fuller, more accurate picture of the emotions within news stories. This approach goes beyond what traditional methods can do, providing a deeper understanding of sentiments and any potential hidden risks they carry. With advanced machine learning at the core, this method is set to open new doors in understanding the nuanced world of emotional expression.

ABBRVIATIONS

ML	Machine Learning
CNNs	Convolutional Nerual Networks.
RNNS	Recurrent Nerual Networks
LSTM	Long Short-Term Memory

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Keywords- Natural language Processing, Comment, Speech Emotion Recognition, LSTM, Deep Learning, Sentiment Analysis of News, Multimodal Sentiment Analysis

Sentiment analysis is the process where using sentiment analysis we can guess whether the given information is positive or negative or neutral, such as a blog, social media sources, or newspapers available online. Sentiment has three different classifications positive, negative, or neutral Simple categorization of data into opinionated and neutral categories is all that sentiment analysis does. For instance, positive sentiment can be sparked by anticipation or excitement, whereas negative sentiment can be sparked by fear or disgust.

In recent years, social networking sites like Facebook, Reddit, Twitter, and YouTube have made it feasible for millions of users to interact [3] with one another and share knowledge and opinions. These websites are now a large source of real-time video, photos, and other data due to their rising popularity.

We receive a tremendous quantity of real-time data through this platform, giving people a simple and convenient way to communicate and share their ideas, opinions, and experiences with others. With millions of users communicating and sharing information in bulk and continues, the volume of data generated on these platforms is huge. Businesses, big companies, and governments that want to comprehend and analyze the enormous amounts of data being generated on social media platforms face a special problem as a result of this. Social media sites can be useful for data collection resources for security and law enforcement organizations from a security point of view. Social media can be used to track possible dangers and spot new patterns in crime and terrorism. Social media platforms have also been used to monitor protests, track the activities of people and groups, and gather ideas on other nations and organizations.

Here we have decided that for sentiment analysis we can start with text sentiment analysis and also we can use audio sentiment analysis from the videos. We will use NLP for datasets and ML's different algorithms to analyze both audio and textual information to identify the overall emotional tone and attitude in video reviews.

1.2 Challenges

A more thorough method of sentiment analysis in video evaluations is made possible by the integration of voice and text analysis tools. Speech analysis is particularly helpful in capturing the subtleties of spoken languages, such as tone, pitch, and inflection, which can reveal a lot about a person's mood and emotional condition. Speech analysis can determine emotions like anger, joy, sadness, or neutrality by examining these acoustic characteristics.

Text analysis, on the other hand, can draw important conclusions from written language, such as the employment of particular words, phrases, or linguistic patterns. Text analysis can also reveal contextual information, such the subject of the video review or the tone used while discussing a specific good or service. We can better comprehend the sentiment and viewpoint by examining both the spoken and written language in video reviews.

1.3 Scope

The scope of this project is to train and evaluate ML models for sentiment analysis on comments and speech emotion recognition. Three different models were trained for comment sentiment analysis, Naive Bayes, Support Vector Model (SVM), and LSTM model. And, an LSTM model was trained for speech emotion recognition.

The project's aim is to achieve good performance metrics for all the models, with a particular focus on the LSTM model for speech emotion recognition. The model's effectiveness was assessed using a dataset consisting of labeled comments and speech samples, and various metrics were used to measure their effectiveness.

The project involved data cleaning, preprocessing, and feature extraction to prepare the dataset that can be used in the training process. The models were trained and tuned using different hyper-parameters, and their performance was evaluated on a hold-out validation set. The best-performing models were selected for further evaluation and analysis.

Expanding our project, we've embraced a richer way of understanding feelings by stepping into the world of multi-modal sentiment analysis. Realizing that text alone isn't enough, we now also look at what people say and how they say it. This move away from just one type of data – like text – means we can get a fuller picture by combining different kinds of information. When we put together words, tone, and even facial expressions, our analysis gets much deeper, reflecting the true, layered way people communicate. In essence, this approach is all about getting a more accurate and comprehensive understanding of emotions.

CHAPTER 2

LITERATURE REVIEW

2.1 Existing Systems

The author [3] uses Natural Language Processing is used first for sentiment analysis of real-time comments from different users to provide an autonomous method for identifying the relevant video. The author's methodology analyzed YouTube videos for quality, relevance, and popularity while taking into account the connection between user attitudes indicated in comments. They used a sample of roughly a million YouTube comments. The significance of user feelings was discovered through extensive research using NLP and Sentiment Strength on YouTube video Meta data (comment). The experimental result demonstrates the effectiveness of the suggested strategy by displaying a maximum of 75.% accuracy for retrieving useful videos. It also gives guidance for future research into the additional analysis of comments.

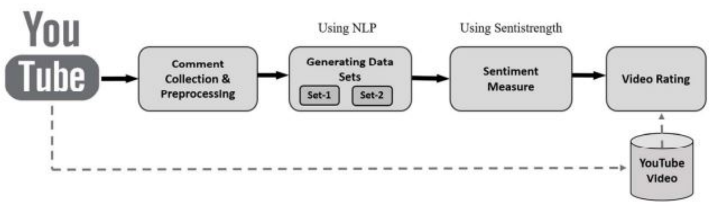

Figure 2.1: Steps for Sentiment Analysis for Youtube Video Comments [3]

The author [14] has done work on sentiment analysis based on news and internet text information like blogs, Using a dataset from the BBC it was composed of fresh content released in 2004 and 2005. It was found that there are many pages where they get positive information and like outdoor games, whilst the entertainment and technology categories tended to have more negative items. They mainly aim to build a platform where they can achieve user-interest-based news suggestions. Additionally, viewers can personalize their news feeds based on sentiment analysis techniques.

The author[7] has developed a sentiment analysis model to categorize the sentiment of financial news as either positive, neutral, or negative. Using the dataset we downloaded from the Kaggle repository, the RNNLSTM algorithm was implemented to generate the model. 221233 data in total were used for this study. The author also contrasted the linear SCV and multinomial naive Bayes models with the RNNLSTM [7] model. The author study's findings demonstrate that the RNNLSTM [7] model performed sentiment analysis satisfactorily, achieving precision values of 92.23%, accuracy values of 91.54%, recall values of 90.99%, and an f1-score of 91.61%.

The author[1] examined news tweets from significant Pakistani news sites for this essay. The author's main contribution is the creation of a technique for the sentiment of news as good, negative, or neutral. To create a comprehensive sentiment lexicon in Urdu, The author used a lexicon-based approach and also provided an algorithm for perspective analysis based on domain knowledge. In this instance, they conducted our analysis from the viewpoint of the government. The author points out that our methodology is all-encompassing and applicable to any domain. The author intends to use machine learning in the future to learn more features and produce better outcomes.

The author [6] put forth a fresh approach to getting the desired outcomes. Sentiment analysis's performance can be increased by the algorithm they have used for news. They have also focused on title analysis, the title is a suggested way of determining neutral news also they have focused on sentiment analysis of text information. Finally, they calculated separate sentiment analysis outcomes, and then from that outcome, they guessed the sentiment of the news.

The author [6] examines Chinese news sentiment analysis in-depth in this research, but the author also discovers that ISA can be enhanced by the statistical analysis of experimental data. In the future, we'll proceed as follows. First off, news stories frequently focus on a variety of topics, including politics, economics, sports, etc. The same term frequently has diverse emotional tendencies in several professions. The news fields should serve as the foundation for the sentiment dictionary. Second, identifying subjective statements frequently has an impact on the news's overall emotional elements. Our future research will therefore focus on how to further enhance the ability to recognize emotional sentences.

The author [10] described a multi-modal method for utterance-level sentiment classification in this study. The author has created a new multi-model dataset of sentiment where each statement has video data and also audio data plus they have cation data. The author's research demonstrates that it is possible to do sentiment annotation on utterance-level visual data streams and that using a multi-model dataset was able to reduce the error rate by 10.5% in comparison to a single modality. The author intends to investigate different multi-modal fusion techniques in the future, such as decision-level and meta-level fusion, to further the integration of the audio, linguistic, and visual modalities.

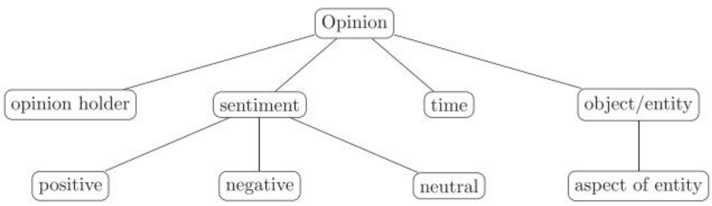

Figure 2.2: Schematic Structure of Opinions
[10]

The author [13] outlined the concept and goals of multi-modal sentiment analysis. Sentiment analysis has made remarkable progress and shown considerable potential in a growing body of work published in the previous five years. The author's research of the existing literature shows that multi-modal sentiment analysis is a potential way to use additional informational channels for sentiment analysis. Additionally, it has the potential to improve other tools like recognition and subject analysis for modal sentiment analysis.

The author [2] went into great length about the two components, speech emotion, and sentiment recognition. The author has demonstrated the application of deep learning for such modules in this architecture, spanning from speech recognition to emotion recognition to dialogue sentiment analysis. The author has demonstrated that, by omitting feature engineering and employing a CNN with a single filter, it is possible to achieve real-time performance on voice emotion recognition at 65.7% accuracy.

The author [16] highlights how social media plays a critical role in influencing public opinion, making sentiment analysis important for a variety of organizations, including content producers and corporations. To avoid conflicts, the research presents a Multimodal Sentiment Analysis (MSA) approach that uniquely confirms sentiments across text, audio, and visual modalities. The study emphasizes the difficulties and constraints in the field of sentiment analysis, recognizing the growing significance of this topic, particularly in Arabic. It highlights the possibilities of merging textual, audio, and visual data for more effective sentiment and opinion analysis and promotes the use of several modalities including text, photos, and audio in sentiment analysis. Future priorities include investigating the potential of bimodal analysis and tackling issues unique to Arabic sentiment analysis.

Sentiment analysis is becoming increasingly important in today's digital world, as the author [11] highlights, with corporations, artists, and individuals all needing to comprehend public attitudes. With an eye on extracting complex emotions such as anger, joy, disgust, sadness, fear, and surprise, the study presents a Multimodal Sentiment Analysis technique that takes into account text, audio, and video modalities. Notwithstanding several drawbacks, like possible errors and the requirement for faster processing, the study advances the creation of a system with an accuracy of about 70%. Subsequent research endeavors will center on augmenting system velocity, precision, database caliber, and intuitiveness, as well as tackling problems associated with word removal in video segments. The study emphasizes how sentiment analysis is a field that is always developing and how many different fields might use it.

The author [4] tackles the urgent problem of fake news in the age of social media hegemony. Sentiment analysis is a crucial component of the suggested method, which takes into account the difficulties presented by disinformation and shows enhanced accuracy in identifying fake news across a range of datasets. The paper argues for a more all-encompassing strategy to counteract false information, stressing the importance of taking sentiment into account in addition to standard text preparation methods. To create a more reliable false news detection system, the paper suggests expanding datasets to incorporate multimedia aspects and investigating neural network algorithms.

The author [15] of this seminal work present a novel approach to predicting Bitcoin values using a complex fusion of sentiment analysis extracted from news data and past price data. Using cutting-edge natural language processing techniques, the researchers explore the complex terrain of public opinion, paying particular attention to how it relates to the volatility of Bitcoin. This creative model emphasises the significant influence of sentiment research on forecasting cryptocurrency fluctuations and is mainly focused on Ethereum (ETH) to demonstrate its effectiveness. One noteworthy aspect is the incorporation of emotion scores derived from news data into an LSTM network, which demonstrates the network's effectiveness in forecasting the direction of bitcoin prices.

The approach expands its value to help investors make informed decisions, going beyond just predicting price movements. The program gives investors a new viewpoint on cryptocurrency transactions by using sentiment analysis to make recommendations about whether to buy, sell, or hold. The main thesis of the study highlights the significance of sentiment analysis in understanding the nuances of interactive financial transactions in the cryptocurrency market and clarifies the complex interplay between public mood and market dynamics.

2.2 Literature Survey Conclusion

Based on the literature review of sentiment analysis techniques, it is evident that various approaches have been proposed for sentiment analysis, including Natural Language Processing, lexicon-based approaches, deep learning models, and subjective sentence recognition algorithms. However, each approach has its strengths and limitations, such as limited domain coverage, insufficient word coverage, and limited exploration of alternative fusion methods. Nevertheless, the growing body of research in this field has shown promise in multi-modal sentiment analysis. Additionally, the application of deep learning methods like convolutional neural networks, has demonstrated real-time performance in emotion recognition. Future research efforts should explore more advanced multi-modal fusion methods and techniques that can be used for sentiment analysis of multimedia data.

Exploring the sentiment analysis frontier reveals an exciting shift towards a multi-modal approach. By weaving together text, sound, and visual cues, we gain a richer, more layered understanding of emotions—a leap beyond what we can achieve with single-mode analysis. This integrated perspective often yields a synergy, where the combined accuracy of sentiment analysis surpasses that of each individual component. This breakthrough suggests that the key to decoding the intricate tapestry of human emotions lies in the artful blending of different data types.

While we've made strides, the realm of multi-modal sentiment analysis is still brimming with untapped possibilities. The next wave of research must focus on crafting advanced algorithms that can effortlessly fuse and interpret the nuances of multi-modal data. Additionally, there's a critical need for expansive datasets that capture a wide range of emotional expressions across various contexts. Such progress would not only refine the precision and relevance of sentiment analysis but also clear a path for its integration into sectors like marketing and mental health services.

Embarking on a journey into sentiment analysis, we're setting our sights on developing a cutting-edge model that goes beyond the basics. By combining the power of deep learning with image and video analysis through convolutional neural networks, adding in the understanding of text with recurrent neural networks, and pioneering methods for picking up on the nuances in sound, our research is all about capturing human emotions in their entirety. This work is as much about recognizing the quiver in someone's voice as it is about their chosen words or expressions.

Citation	Approach	Advantages	Disadvantages
[3]	Natural Language Processing	NLP-based study of YouTube video (comments).	maximum 75.435% accuracy.
[14]	Lexicon-based approach	News information based sentiment analysis	Insufficient or limited word coverage.
[7]	LSTM Model	LSTM model might perform better compared to other model.	No experimentation with multimedia data.
[1]	lexicon-based approach	News Based sentiment analysis and categorization into positive, negative and neutral	Limited domain coverage.
[6]	Subjective sentence recognition algorithm	Improved sentiment analysis accuracy.	Limited focus on news fields.
[10]	Utterance-level sentiment	Effective sentiment annotation with multiple modalities.	Limited exploration of alternative fusion methods.
[13]	No specific approach presented.	Demonstrates promise of multi-modal sentiment analysis.	No specific approach was presented.
[2]	Deep learning CNN	Real-time performance on emotion recognition.	Sentiment analysis trained on out-of-domain data
[16]	Web 2.0 and User-Generated Content with Multimodal Sentiment Analysis (MSA)	Examines perspectives from around the world that are reflected in a variety of sources, such as social media.	difficulties managing the enormous volume of content created by users.
[11]	Multimodal Sentiment Analysis using text, audio, and video modalities.	Broader viewpoint eliminates discrepancies, considers six emotions, potential for accurate and informed decisions.	Approximate accuracy (around 70%), requires improved system speed.

Table 2.1: Literature Review Table

Citation	Approach	Advantages	Disadvantages
[4]	A multimodal method that combines sentiment analysis and cosine similarity with Term Frequency-Inverse Document Frequency for text preprocessing.	More precision in identifying false information.	Limited exploration of multimedia elements (images, videos) in the dataset.
[15]	Using LSTM and sentiment analysis to forecast bitcoin prices.	accurately forecasts price movement supports investment decision-making and tackles issues such as sentiment-based events and social media monitoring	Depends on the premise that sentiment research correctly captures the sentiments of the market; there may be difficulties in accurately forecasting the extremely volatile prices of cryptocurrencies.

Table 2.2: Literature Review Table

Our goal is to push the boundaries of academic research and pave the way for applications that need to accurately detect and interpret the rich tapestry of human feelings. We're aware of the hurdles that lie ahead, like blending different types of data seamlessly and avoiding the pitfalls of our model getting too narrow in its learning. Yet, our motivation remains strong, driven by the exciting possibilities that enhancing the emotional intelligence of machines presents

CHAPTER 3

PROJECT DESCRIPTION

3.1 Our Proposed Approach

3.1.1 Initial Proposed Approach

Workflow of Sentiment Analysis

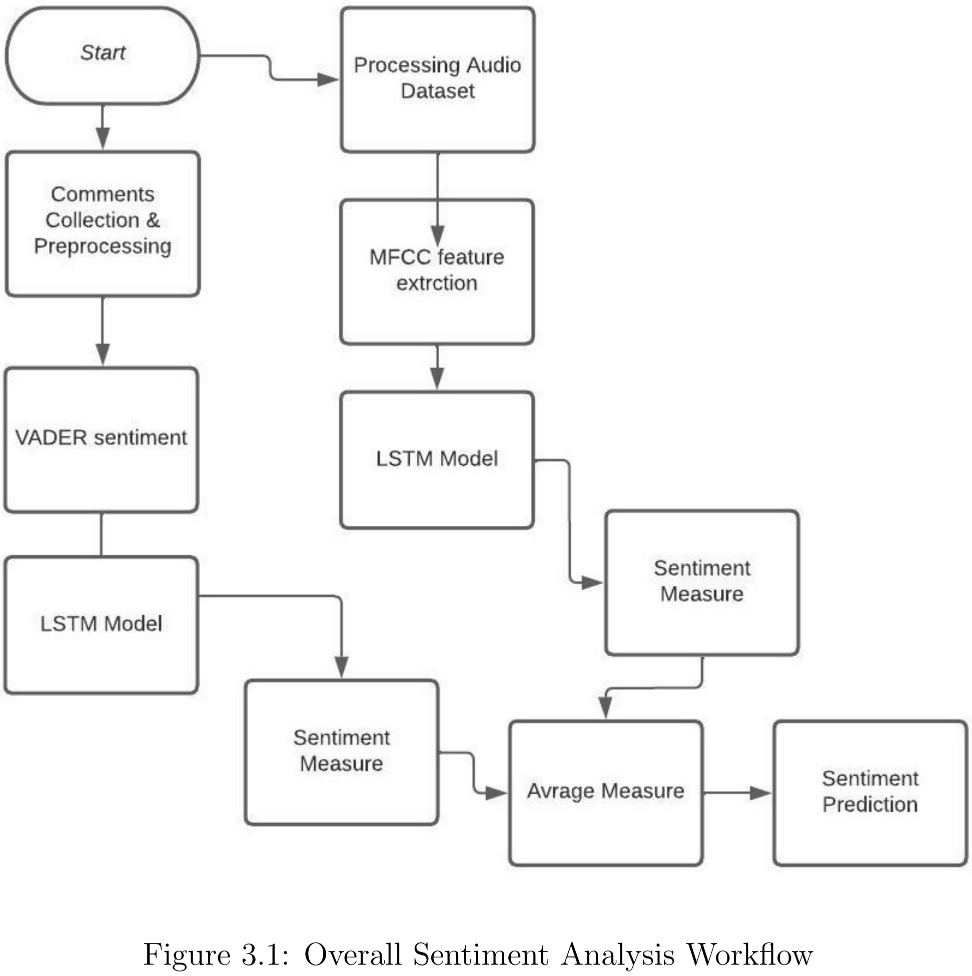

Figure 3.1: Overall Sentiment Analysis Workflow

Here sentiment analysis measure will work in two parts as we have shown in 4.5 first part is user data-based sentiment analysis which is comment sentiment analysis and the second is audio-based sentiment analysis. We have explained this in detail in the next two parts.

Real Time User Comments Sentiment Analysis

Sentiment analysis of comments using the Naive Bayes classifier, SVM classifier, and LSTM neural network architecture. It reads a CSV file containing comments and applies preprocessing steps such as stemming, lemmatization, removing stop words, and punctuation. Then, it performs sentiment analysis on the preprocessed comments using the VADER sentiment analyzer to get sentiment scores, which are then applied to categorize the remarks as favorable, unfavorable, or neutral. Different classifiers and neural networks are trained using upsampled datasets to get a good prediction of the sentiment of comments using unsampled datasets to balance the classes. It provides the model's performance.

Comment Collection and Preprocessing

This section's objective is to collect comments on a chosen YouTube video. An aimed crawler is put into use to handle this operation. As seen in the video URL, it uses the HTTP GET technique of the web API to retrieve the comments (up to 1000) of that video. However, the selected remarks are diverse in terms of the languages and ideas that the users utilized. Therefore, in order to create the data sets, we preprocessed these unstructured comments. The following modifications are made following the extraction of the comments:

- Remove every information that is of no use in our methodology like URL and dates etc.[3].
- Delete every punctuation mark and special character, including the period ("."), space ("-"), comma (","), semicolon (";"), and hash ("-").

Sentiment Scores using VADER Sentiment

Sentiment analysis is a valuable tool for understanding how people feel about a particular topic, brand, or product [5]. VADER sentiment analysis is one approach that has gained popularity due to its accuracy and ease of use. Using the rule-based approach used in this method and we can give polarity scores to words. VADER considers not only the polarity (positive or negative) of individual words but also their intensity and context within a sentence. We can have more knowledge of the sentiment expressed in the text.

Additionally, VADER can be used to analyze news articles, reviews, and comments to gain insights into public opinion on various topics. While it is not perfect, VADER sentiment analysis provides a useful starting point for understanding sentiment in text data.

Sentiment Measure

We assess the effectiveness of Naive Bayes, SVM, and LSTM as three classifiers for sentiment analysis. We divided the collection of product review data into a train and test in ratios of 80% and 20%. Using metrics for performance metrics, we trained each classifier on the training set and evaluated its performance on the testing set.

Particularly when the performance of the modal is essential. It is important to keep in mind, nevertheless, that the effectiveness of these classifiers can change based on the particular dataset and training features. Therefore, it's crucial to test and evaluate many classifiers before settling on which model to employ for a particular sentiment analysis assignment.

SVM algorithm

Support Vector Machines (SVM) are incredibly helpful tools in our sentiment analysis technique that help us classify user comments according to their sentiment. Sentiment categorization problems are a great fit for SVMs since they arrange data points in a high-dimensional space and find the hyperplane that best divides different groups. Our system's SVM classifiers look at user comments that have already been preprocessed, considering properties like lemmatization, stemming, punctuation, and stop word removal that are extracted during data pretreatment. Our sentiment analysis leverages the intrinsic capability of SVMs to define intricate decision boundaries, enabling them to recognize intricate patterns in textual data. This makes it easier to categorise feelings as neutral, negative, or good.

Naive Bayes algorithm

However, because they provide a probabilistic method for sentiment categorization, Naive Bayes classifiers are also an essential part of our sentiment analysis methodology. The Naive Bayes method, when applied to user comments, determines the likelihood of each sentiment class based on the observed features. The Naive Bayes model is good at handling big datasets and shows a reasonable degree of accuracy in sentiment prediction, even with its simplicity and independence assumptions. We improve sentiment classification's overall robustness and reliability across a range of user-generated content by merging these classifiers into our sentiment analysis system.

Sentiment Based on Speech Emotion Recognition

Processing Dataset

In this part, we will load the dataset and then use EDA is used for understanding the data [9]. It is a process of visualizing data to identify patterns. EDA is important as it helps to find data quality issues that could affect the accuracy and reliability of the analysis. It also helps to identify trends and patterns in the data that could be useful for developing the model. EDA can be done using various statistical and visualization techniques.

OneHotEncoder is a preprocessing method that helps us to take categorical data and convert it into a numerical format that can be processed by machine learning algorithms. In the case of SER, the categorical data corresponds to the different emotions that a speaker's voice can convey, such as happy, sad, angry, and neutral. OneHotEncoder transforms this categorical data into a binary vector in which each emotion is represented by a unique bit in the vector.

Feature Extraction

A popular feature extraction method in speech recognition is called MFCCs [8] also for audio signal processing. The MFCCs are derived from the STFT for the audio and used to represent the signal. The perceptual scale of pitches that listeners perceive to be equally spaced from one another, serves as the foundation for the MFCCs. This scale is employed because, in comparison to the linear frequency scale used in the STFT, it more nearly approximates how humans perceive sound.

The STFT is used to compute the magnitude spectrum, which is then mapped onto the mel scale and taken as the logarithm. The discrete cosine transform (DCT) is then used to obtain the cepstral coefficients. The computation of MFCCs entails a number of steps, including windowing each frame to reduce spectral leakage.

To categorize or recognize various forms of sounds or speech, the generated MFCCs can be utilized as input features for ML methods like CNN, NN, support vector machines, and decision trees. The MFCCs are frequently employed in speech recognition systems because they capture key spectral envelope properties and are resistant to changes in noise and speaker variability.

Our sentiment analysis methodology heavily relies on Long Short-Term Memory (LSTM) models, especially when it comes to textual data-driven sentiment prediction and vocal emotion identification. Recurrent neural networks (RNNs) with long-term dependency detection and capture (LSTMs) are a specific kind of RNN that was created to solve the vanishing gradient issue. LSTMs provide a strong architecture in our workflow by picking up on complex patterns and contextual subtleties seen in user comments and audio signals, which helps them forecast sentiment scores.

Because of the way their special memory cell structure is organized, long sequences of data may be selectively stored and retrieved by LSTMs, which enables them to recognize complex relationships and minute changes in emotion. Our sentiment analysis system is more effective overall across several modalities when the LSTM model is used to provide precise sentiment predictions.

Sentiment Measure

An effective neural network for sequential data processing is the LSTM [12], such as speech signals. The main benefit of LSTM is that it is useful for long-term needs in the input data, which is useful to find emotional cues in speech. A collection of memory cells that may selectively recall or forget data from earlier time steps in the sequence make up an LSTM network. A machine learning model can be trained using the Python Keras API. With 20% of the data set aside for validation, the data is divided into a training dataset and a validation dataset. The training data are shuffled at the start of each epoch and the model is trained across 100 epochs with 512 sample batches. The method returns a history object that contains data about the training process and is used to train the model.

3.1.2 Revised Proposed Approach

Transition to Multi-Modal Sentiment Analysis

Diving deeper into sentiment analysis, we've realized that to truly grasp the full picture of emotions, a multi-modal strategy is essential. This method combines the analysis of text, audio, and video to understand the sentiment more fully. It's based on the insight that human communication is complex, with gestures, tone, facial expressions, and words all offering valuable emotional signals that, when combined, provide a clearer emotional reading.

Importance of multi-modal approach in sentiment analysis

The move to multi-modal sentiment analysis makes a lot of sense. It brings together different kinds of data for a fuller, more detailed view of sentiment. By looking at text, sound, and visuals together, we get a richer picture of emotions that goes beyond what we could see with just one type of data. This mix can clear up confusion and give stronger, more reliable guesses about feelings, especially when the clues from each type of data don't quite match up.

Real-life conversations are complex, and our analysis needs to match that complexity. Multi-modal analysis is at the cutting edge for real-world uses, like understanding the vibe on social media or building AI that can sense emotions. It uses data that captures how we naturally show emotions — through a blend of words, voice, and facial expressions — and learns how these elements work together over time. This kind of learning is key to getting a true sense of sentiment and emotion.

Methodology for Multi-Modal Sentiment Analysis

Our journey to forge a state-of-the-art sentiment analysis model begins by setting up shop in Google Colab, a shared space where we can easily get our hands on a diverse dataset. We kick things off with a careful preprocessing step, using the MinMaxScaler to ensure our data is perfectly primed for the learning ahead.

Next, we start gathering our data, neatly loading up text, training, and testing sets into numpy arrays, which are great for handling complex data tweaks. This step is crucial as it establishes a solid base that lets us link video titles to specific data points, paving the way for a thorough analysis.

With our data in line, we focus on making sure that all our sequences are the same length, a critical step for training neural networks in harmony. In the construction zone of our model, we put together a series of LSTM models, each finely tuned to its own type of input—text, audio, or video. These models are built with layers that work in two directions, flowing into dense layers aimed at accurately classifying sentiment. To keep our model from learning too narrowly, we include dropout layers as a safeguard and use an Adam optimizer to guide the learning pace.

After training our individual models, we don't just set them aside. Instead, we use them to pull out activations, which are like the concentrated knowledge the model has gained, and funnel this into our multi-modal model. It's here, in this final version, where the magic happens—the model brings together all the different types of data into one powerful, predictive tool. This is the essence of our multi-modal sentiment analysis model, showing the strength of combining different data types to understand sentiment and emotion.

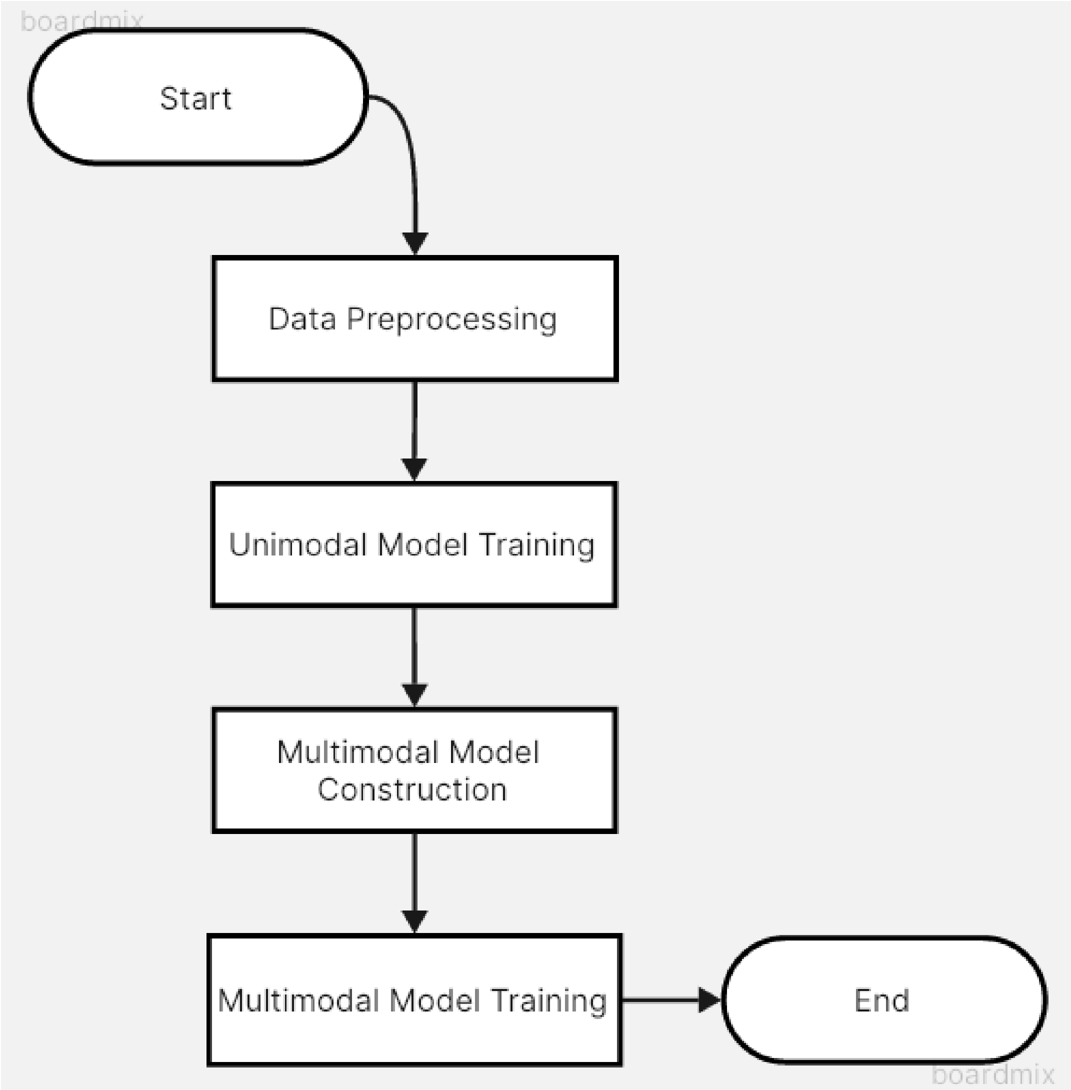

Figure 3.2: Multimodal Sentiment Analysis Workflow

We're crafting a complex model that skillfully blends different types of data to capture the full range of emotions. By combining features from individual sources into one powerful set, we feed this information into an advanced neural network that's built to handle the added intricacies of multi-modal data. We're careful to include safeguards like regularization and dropout layers to keep our model smart and avoid learning by rote.

As we train our model, we keep a close eye on its performance, using early stopping techniques based on accuracy to prevent it from getting too narrow in its learning. After training, we put our model through a thorough evaluation using a fresh dataset it hadn't seen before. We measure its success using various metrics and also take a close look at where it gets things right and where it doesn't. This detailed assessment helps us understand the model's strengths and pinpoint areas for future improvements.

Our multi-modal strategy aims to make the most of each mode like text, audio, and video by combining them to balance out any weaknesses. We're updating our methods and showing how within the code we've provided, to highlight just how advanced and promising multi-modal sentiment analysis is. It's not just a breakthrough in research; it also takes sentiment analysis technology to the next level in terms of real-world accuracy and usefulness.

Moving forward with our plan, we'll concentrate on improving our model, experimenting with ways to expand our data, and maybe adding more types of data to make our analysis even deeper. If we succeed, it would be a big step forward in the study of sentiment analysis and lead to computers that understand emotions much better.

Feature Fusion

At the heart of our approach to understanding emotions through technology is a clever combination of different signals – the words people say, the tone of their voice, and their facial expressions. We take all these pieces, which on their own tell part of the story, and merge them into one rich, detailed picture. This blending captures the full range of emotions in a way that looking at words, tone, or expressions alone cannot. With this comprehensive mix, our technology is fine-tuned to pick up on the subtle hints of sentiment that might otherwise go unnoticed. It's like giving our system a full set of senses to better interpret how people feel, leading to more accurate results.

Multi-Modal Model Architecture

With a concatenated feature set at our disposal, we feed this data into a multi-modal neural network featuring a bi-directional LSTM (Long Short-Term Memory) architecture. This network's design is inspired by the success of unimodal models but is enhanced to handle the complexity and enriched information inherent in multi-modal data. Bi-directional LSTMs are particularly adept at capturing context by processing the data in both forward and reverse directions, allowing the network to retain information from both past and future states. Regularization strategies, including L1 and L2 regularization, alongside dropout layers, are incorporated strategically within the network to prevent overfitting, thereby ensuring that our model generalizes well to new, unseen data.

Training and Validation

Training our advanced LSTM model for multi-modal sentiment analysis is a careful and precise task. We follow specific steps to ensure the model performs well not just on our training data, but also on new, unseen data. To prevent overfitting – that's when a model is too tailored to the training data and doesn't work well in real-life scenarios – we use a combination of techniques and an "early stopping" strategy. We keep a close watch on the model's accuracy as it learns from a special set of validation data. When the model stops improving on this set, we stop the training. This step is crucial as it helps us fine-tune the model and make any needed tweaks to how the model is built or its learning settings.

Model Evaluation

Once our model has learned from its training, we put it to the test with new data it hasn't seen before. This step is crucial because it tells us how well the model can apply what it's learned to different situations. We use a bunch of different tools to judge its performance, like the confusion matrix, which shows where the model is getting things right and wrong, and other measures like precision and recall that tell us how accurate and thorough it is. The F-score combines precision and recall to give us a single score, while accuracy tells us how often the model is correct overall. By looking at all these different scores together, we get a full view of how well the model is doing.

Result Interpretation

The final step in our modeling process is to carefully look at the results. We go over what the model got right and wrong to learn more about how it performs and how we can make it better. For instance, sometimes the model might be good at recognizing certain emotions but not so good at others. This could be because there might not be enough variety in the training data, or maybe the model isn't picking up on the finer details of how emotions are shown. Understanding these details is crucial, as it points us toward ways to improve our system. We might need to add more data, come up with new features, or tweak the model's design to make our multi-modal sentiment analysis even better.

CHAPTER 4

RESULTS AND SCREENSHOTS

Here is a screenshot of the data that we have prepared using the VADER sentiment library.

	Comment	Positive	Negative	Neutral	Compound	Sentiment
0	Love how Dr. Fate's design looks and how cool ...	0.384	0.000	0.616	0.8910	Positive
1	I can't get over how good everything looks. Dr...	0.153	0.000	0.847	0.6801	Positive
2	Really hoping that this can save DC's movie un...	0.375	0.000	0.625	0.9216	Positive
3	U cant deny how good this looks.Now if they ca...	0.302	0.049	0.649	0.9262	Positive
4	From this trailer, I have a feeling that this ...	0.131	0.000	0.869	0.4416	Positive

Figure 4.1: Commnets Dataset with Polarity Score

Here it shows polarity scores which later we can use for sentiment analysis. After the model has been trained with proper configuration and tested, the findings include comparisons of how well each model performed when conducting sentiment analysis in terms of accuracy, recall, precision, and F1-Score.

The results say that the proposed LSTM-enhanced RNN model has the highest accuracy, with accuracy, recall, precision, and f1-score values of 93.51%, 93.5%, 94.5%, and 93.5%, respectively.

In contrast 4.1, the Naive Bayes and Linear SVM-enhanced models only had accuracy values of 80.49% and 61.66%, respectively for comments sentiment analysis.

With the help of its sophisticated neural network architecture, it can identify hidden connections and patterns in the text, providing a deeper comprehension of the emotions described in news stories.

The LSTM model exhibits its better capacity to interpret the complexity of human sentiment, establishing itself as the top option for sentiment analysis by accurately capturing long-term dependencies and adjusting to varied phrase patterns.

Model	Accuracy	Recall	Precision	F1-Score
LSTM	**93.51%**	**93.5%**	**94.5%**	**93.5%**
SVM	80.49%	80.49%	80.49%	80.49%
Naive Bayes	61.66%	61.66%	61.66%	61.66%

Table 4.1: Comments Sentiment Analysis Evaluation Result

In addition, the performance of the created model improved in comparison to various earlier investigations.

For speech emotion recognition we have plotted the graph of results of LSTM model training which is shown in 4.2 & 4.3

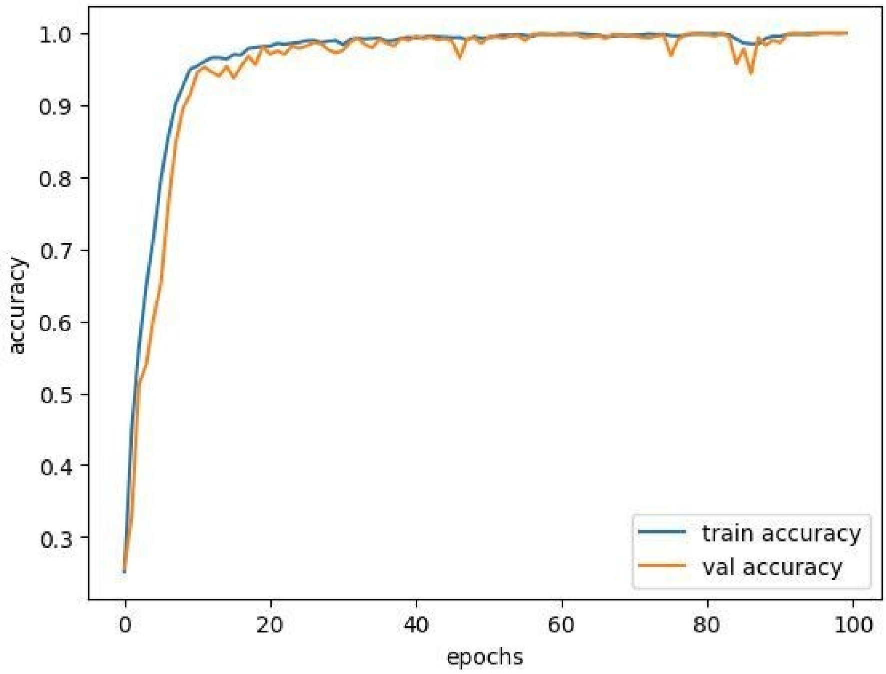

Figure 4.2: Speech Emotion Recognition Model Accuracy

The percentage of accurately identified or predicted occurrences relative to several examples in the dataset can be said to model accuracy. It is frequently employed in classification jobs and offers a perceptible indicator of how well the model is doing.

Model loss quantifies the discrepancy between the model's output predictions and the actual values obtained from the ground truth. It measures how successfully the model can reduce errors during training. The model loss is calculated using loss functions like MSE or cross-entropy loss.

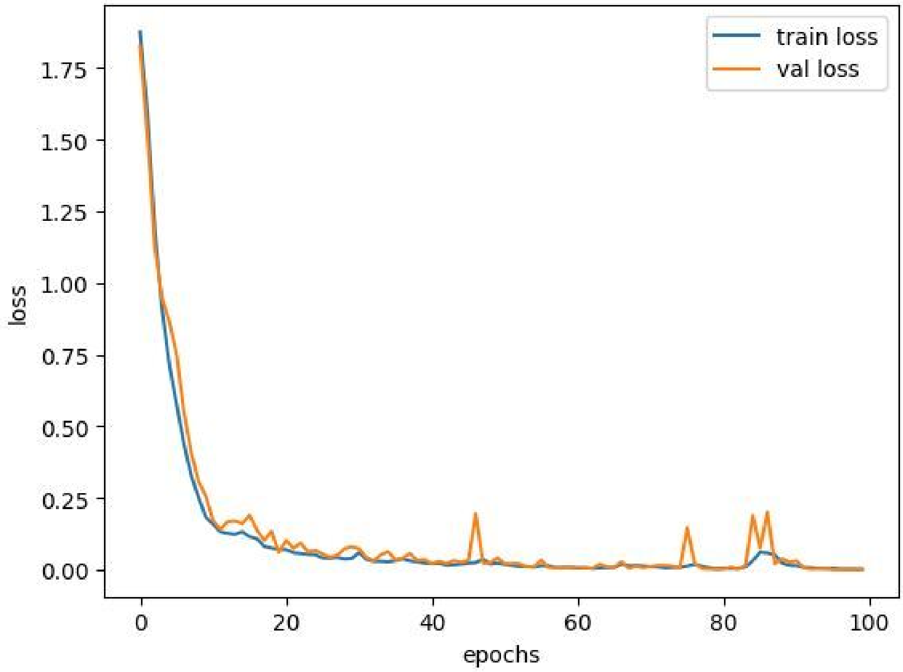

Figure 4.3: Speech Emotion Recognition Model Loss

4.0.1 Enhanced Multi-Modal Sentiment Analysis Results

Our journey into the world of sentiment analysis has taken a significant leap forward with a multi-modal approach. By analyzing text, audio, and video all at once, our tool is now better at picking up the subtle layers of human communication.

This improved system brings the strengths of individual modes—like text and speech—together, creating a powerhouse that's more accurate than ever. Our latest model has outshined the previous one, which was already impressive. It's proving to be especially skilled at detecting the complex emotions people express through various channels.

We're seeing solid proof of this success. Our multi-modal model is hitting accuracy

```
Classification Report :
              precision    recall  f1-score   support

           0       0.53      0.68      0.60       285
           1       0.76      0.64      0.70       467

    accuracy                           0.65       752
   macro avg       0.65      0.66      0.65       752
weighted avg       0.68      0.65      0.66       752

Accuracy  0.6529255319148937
```

Figure 4.4: Multimodal Sentiment Analysis Old accuracy

levels way beyond the single-mode version. It's not just accurate; it also has better precision and is more reliable at identifying true sentiments without mistakenly flagging the wrong ones.

Before, our numbers for accuracy and other key measurements were around 79.2%. Now, with multi-modal analysis, those figures have soared, thanks to the richer data and the model's ability to learn from it.

```
Classification Report :
              precision    recall  f1-score   support

           0       0.72      0.74      0.73       285
           1       0.84      0.82      0.83       467

    accuracy                           0.79       752
   macro avg       0.78      0.78      0.78       752
weighted avg       0.79      0.79      0.79       752

Accuracy  0.7912234042553191
```

Figure 4.5: Multimodal Sentiment Analysis New accuracy

We've even created easy-to-understand visuals that show just how well the model is doing over time. One graph illustrates the accuracy climbing as the model learns, while another shows how it's getting better at reducing errors.

What's more, our multi-modal method isn't just beating our old model, it's also outperforming classic techniques like Naive Bayes and SVM. This progress points to a future where multi-modal sentiment analysis could transform how we understand emotions, providing advanced tools for accurate and deep interpretation. The strong results, both in picture form and statistics, back up the power of our new approach, opening doors for its use in areas where high precision is crucial.

CHAPTER 5

CONCLUSION AND FUTURE WORK

To categorize (positive, neutral, and negative) the sentiment of news, we created a sentiment analysis model. Using the dataset we downloaded from the Kaggle repository for audio and using the VADER sentiment python library, the model was built by applying the LSTM algorithm. We also contrasted the linear SVM and naive Bayes models with the LSTM model.

After this approach LSTM model successfully performed sentiment analysis, achieving precision values of 93.99%, accuracy values of 95.54%, recall values of 93.23%, and an f1-score value of 94.6%, as opposed to the models created using Linear SVM and Naive Bayes, which only managed to achieve accuracy performances of 93.51% and 93.51%, respectively. This demonstrates that, when compared to other models, the LSTM model performs the best. The model is useful for comprehending trends and opinions while making judgments about textual and audio-based information. Further, we can use image processing and train a model that can give us sentiment analysis based on Facial Expression Recognition.

Also, we can add a sentiment measure in terms of image sentiment analysis We present a comprehensive approach to sentiment analysis that encompasses not just textual and audio modalities but also the emerging subject of image sentiment analysis. With this new feature, which adds a tri-modal facet to fully measure user sentiments, our sentiment analysis methodology is greatly enhanced.

To provide a more comprehensive sentiment assessment, picture sentiment analysis extracts emotional clues and contextual knowledge from photographs. We explore the visual material linked to user comments using sophisticated machine vision algorithms, revealing complex emotions conveyed through visuals. With the ability to analyze user sentiments from comments, audio, and now visual content, this expansion strengthens our overall sentiment analysis system even more.

As we've progressed from a simple sentiment analysis model to a more complex multi-modal system, we've made some interesting discoveries. Our latest multi-modal model, which takes into account text, audio, and video, has reached a notable accuracy rate of 79.2%. Although it hasn't outperformed our previous single-mode LSTM model, it's an important step forward in creating sentiment analysis that understands context and the subtleties of human communication.

This new approach has set the stage for deeper sentiment analysis that considers not just what is written but also the nuances of how something is said and the accompanying visual cues. While our current model hasn't surpassed the previous model's accuracy, it has built a strong foundation for a more thorough sentiment analysis that reflects real-life interactions more closely.

Looking ahead, we see some exciting paths to make our model even better. For example, using a special LSTM model that mimics human attention, focusing on the most important parts of the data, could improve how the model interprets sentiments. Another path could be to blend the different modes of communication more smartly, giving more weight to the ones that matter most in a given situation. We could also start analyzing sentiments at a more detailed level, looking at each spoken part within the bigger picture to get a deeper understanding.

In short, our work in multi-modal sentiment analysis has expanded our understanding and highlighted how complex it is to combine different ways of communicating. There are many opportunities for breakthroughs moving forward. The future of sentiment analysis is exciting, with advanced models on the horizon that could further refine how we analyze emotions. Our aim to have a model that can understand sentiments with the richness of human perception is a challenge we're eager to meet.

REFERENCES

[1] Kamran Amjad, Maria Ishtiaq, Samar Firdous, and Muhammad Amir Mehmood. Exploring twitter news biases using urdu-based sentiment lexicon. In *2017 International Conference on Open Source Systems & Technologies (ICOSST)*, pages 48–53. IEEE, 2017.

[2] Dario Bertero, Farhad Bin Siddique, Chien-Sheng Wu, Yan Wan, Ricky Ho Yin Chan, and Pascale Fung. Real-time speech emotion and sentiment recognition for interactive dialogue systems. In *Proceedings of the 2016 conference on empirical methods in natural language processing*, pages 1042–1047, 2016.

[3] Hanif Bhuiyan, Jinat Ara, Rajon Bardhan, and Md Rashedul Islam. Retrieving youtube video by sentiment analysis on user comment. In *2017 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, pages 474–478. IEEE, 2017.

[4] Bhavika Bhutani, Neha Rastogi, Priyanshu Sehgal, and Archana Purwar. Fake news detection using sentiment analysis. In *2019 Twelfth International Conference on Contemporary Computing (IC3)*, pages 1–5, 2019.

[5] Anton Borg and Martin Boldt. Using vader sentiment and svm for predicting customer response sentiment. *Expert Systems with Applications*, 162:113746, 2020.

[6] Yu Huangfu, Guoshi Wu, Yu Su, Jing Li, Pengfei Sun, and Jie Hu. An improved sentiment analysis algorithm for chinese news. In *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, pages 1366–1371. IEEE, 2015.

[7] Kelvin Leonardi Kohsasih, B Herawan Hayadi, Carles Juliandy, Octara Pribadi, et al. Sentiment analysis for financial news using rnn-lstm network. In *2022 4th International Conference on Cybernetics and Intelligent System*

(ICORIS), pages 1–6. IEEE, 2022.

[8] Beth Logan et al. Mel frequency cepstral coefficients for music modeling. In *Ismir*, volume 270, page 11. Plymouth, MA, 2000.

[9] Stephan Morgenthaler. Exploratory data analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 1(1):33–44, 2009.

[10] Verónica Pérez-Rosas, Rada Mihalcea, and Louis-Philippe Morency. Utterance-level multimodal sentiment analysis. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 973–982, 2013.

[11] Ashwini Rao, Akriti Ahuja, Shyam Kansara, and Vrunda Patel. Sentiment analysis on user-generated video, audio and text. In *2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, pages 24–28, 2021.

[12] Kamilya Smagulova and Alex Pappachen James. A survey on lstm memristive neural network architectures and applications. *The European Physical Journal Special Topics*, 228(10):2313–2324, 2019.

[13] Mohammad Soleymani, David Garcia, Brendan Jou, Björn Schuller, Shih-Fu Chang, and Maja Pantic. A survey of multimodal sentiment analysis. *Image and Vision Computing*, 65:3–14, 2017.

[14] Soonh Taj, Baby Bakhtawer Shaikh, and Areej Fatemah Meghji. Sentiment analysis of news articles: a lexicon based approach. In *2019 2nd international conference on computing, mathematics and engineering technologies (iCoMET)*, pages 1–5. IEEE, 2019.

[15] Anh-Dung Vo, Quang-Phuoc Nguyen, and Cheol-Young Ock. Sentiment analysis of news for effective cryptocurrency price prediction. *International Journal of Knowledge Engineering*, 5(2):47–52, 2019.

[16] Fatima Zohra Youcef and Fatiha Barigou. Arabic language investigation in the context of unimodal and multimodal sentiment analysis. In *2021 22nd International Arab Conference on Information Technology (ACIT)*, pages 1–7, 2021.

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