FAKE NEWS DETECTION

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology

in

Computer Science and Engineering

by

Dhruv Vaidh-19BCE0817

Gunik Luthra-19BCE2285

Anshul Anand-19BCI0065

Under the guidance of

Dr. Swathi J.N

SCOPE

VIT, Vellore.

MAY, 2023

DECLARATION

I hereby declare that the thesis entitled "FAKE NEWS DETECTION" submitted by me, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering* to VIT is a record of bonafide work carried out by me under the supervision of Dr. Swathi J.N.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place : Vellore

Date :18/5/23

Signature of the Candidate

<u>CERTIFICATE</u>

This is to certify that the thesis entitled "FAKE NEWS DETECTION" submitted by **Anshul Anand 19BCI0065, SCOPE**, VIT, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering*, is a record of bonafide work carried out by him / her under my supervision during the period, 01. 07. 2022 to 30.04.2023, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The thesis fulfills the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

Place : Vellore

Date :18/5/23

Signature of the Guide

Internal Examiner

External Examiner

Head of the Department

Software Systems

ACKNOWLEDGEMENTS

We would like to thank Dr Swathi J.N for her continued support and guidance through out this project. We would also like to thank her and Vellore Institute of Technology for providing us with the opportunity to work on this project and explore a domain that incites wisdom and knowledge in us. It was a real delight completing this project and this was really helpful in implementing the things we learnt throught the course degree. We would also lie to thank our parents for giving us the resources required to complete this project.

Student Name

Executive Summary

Fake news detection is a critical task in today's information age, and researchers have explored various techniques to tackle this issue. Two prominent approaches involve utilizing the power of natural language processing (NLP) models, Roberta and RegNet. Roberta is a state-of-the-art NLP model based on the transformer architecture, pre-trained on a vast amount of text data. RegNet is a deep learning model designed for image recognition tasks, but can be repurposed for fake news detection by converting textual inputs into visual representations using techniques like text-to-image encoding. Researchers have developed an ensemble model that leverages both textual and visual information to enhance fake news detection. This hybrid approach provides a comprehensive understanding of the news content, utilizing the linguistic context from Roberta and the visual context from RegNet. This fusion of techniques has demonstrated promising results in accurately identifying fake news, helping to combat the spread of misinformation and promote more reliable information sharing. Moreover, this approach has the potential to be applied in various fields beyond news detection, such as image and video analysis. As technology continues to advance, the use of hybrid approaches may become increasingly common in addressing complex problems that require a multi-faceted understanding.

CONTENTS

Page No.

List of Figures

List of Abbreviations

FND	Fake News detection
MLM	Mass language modelling
NLP	Natural language processing
RNN	Recurrent neural network

1. INTRODUCTION

1.1 THEORETICAL BACKGROUND

The theoretical background of fake news detection lies in the fields of natural language processing (NLP), deep learning, and image recognition.

Roberta is a variant of the transformer architecture, which is a deep learning model designed to process sequential data efficiently. Transformers employ attention mechanisms that enable them to capture the contextual relationships between words in a sentence. Roberta, in particular, benefits from a large-scale pre-training process on diverse text data, which helps it learn general language patterns and semantic representations.

Fake news detection using Roberta involves fine-tuning the model on labeled datasets specifically curated for fake news identification. During the fine-tuning process, Roberta learns to distinguish between trustworthy and misleading content by leveraging linguistic features, such as sentiment, syntax, and semantic cues. Its ability to understand the context and semantics of the text helps in capturing subtle linguistic cues that distinguish fake news from genuine news.

RegNet, on the other hand, is originally designed for image recognition tasks. It employs convolutional neural networks (CNNs) that are capable of learning visual patterns and features from images. In the context of fake news detection, RegNet can be adapted to process textual inputs by converting them into visual representations. This conversion is achieved using techniques like text-to-image encoding, where textual features are mapped onto visual representations.

By treating text as images, RegNet can analyze the visual patterns and inconsistencies present in the text, which can be indicative of fake news. The CNNs in RegNet can extract visual features, detect irregularities, and identify suspicious patterns in the textual representations. This visual context adds an additional dimension to the detection process and complements the linguistic analysis performed by Roberta.

The combination of Roberta and RegNet in a hybrid ensemble model allows for a comprehensive analysis of both the textual and visual aspects of news content. By leveraging the strengths of both models, the ensemble can capture a broader range of features and signals, leading to improved accuracy in identifying fake news.

Overall, the theoretical background of fake news detection using Roberta and RegNet draws upon the principles of NLP, deep learning, and image recognition to create a powerful framework for identifying and combatting misinformation.

1.2 MOTIVATION

The motivation behind fake news detection using models like Roberta and RegNet is driven by the urgent need to combat the spread of misinformation in today's digital era. Fake news has become a significant societal issue, capable of influencing public opinion, creating social unrest, and undermining trust in media sources. The widespread availability of social media and the ease of content sharing has made it challenging to discern real news from fabricated or misleading information. This has led to an alarming proliferation of fake news, which poses threats to democratic processes, public safety, and individual decision-making.

A potential solution to this issue is the use of cutting-edge technologies like deep learning and natural language processing (NLP). In order to analyse text for linguistic patterns and semantic cues related to fake news, models like Roberta have shown impressive abilities in understanding and processing natural language. Utilizing the strength of these models makes it possible to automatically detect false or misleading information on a large scale. Additionally, the application of image recognition models like RegNet for the detection of fake news acknowledges the possibility of visual patterns and irregularities in textual content that point to falsity. By treating text as images, these models can use CNNs to find hidden patterns and identify visual discrepancies that might not be visible through linguistic analysis alone.

The goal of the project is to detect fake news is to offer a workable and scalable solution to stop the spread of false information. Accurately identifying fake news makes it possible to lessen its negative effects, maintain the reliability of information sources, and advance an educated and astute society. Such technology can help individuals, news organisations, social media platforms, and individuals make more informed decisions about the veracity and accuracy of the information they come across, ultimately fostering a more responsible and trustworthy information ecosystem.

1.3 AIM OF THE PROPOSED WORK

Using the combined strength of the Roberta and RegNet models, the proposed work aims to create a cutting-edge system for the detection of fake news. The main goal is to develop a reliable and precise solution that can distinguish and categorise fake news from authentic news articles or textual content. The proposed work aims to take advantage of Roberta's rich contextual knowledge, which can identify complex linguistic patterns and semantic cues related to fake news. The goal is to improve Roberta's ability to spot linguistic cues that are indicative of false information by fine-tuning it on labelled datasets that have been specifically curated for fake news detection. Additionally, the goal is to modify RegNet, which was initially developed for image recognition, so that it can process text inputs by visualising them. This allows for the analysis of visual patterns, irregularities, and suspicious cues in the text, which can complement the linguistic analysis performed by Roberta.

By combining the strengths of Roberta and RegNet in a hybrid ensemble model, the aim is to create a comprehensive framework that can analyze both textual and visual aspects of news content. This fusion of techniques aims to improve the accuracy of fake news detection by capturing a wider range of features and signals.

Ultimately, the aim of the proposed work is to provide an effective tool that can assist in combating the spread of fake news, contributing to a more informed society and promoting the responsible consumption of information. By developing a reliable and scalable solution, the goal is to empower individuals, news organizations, and social media platforms in making informed decisions about the credibility and trustworthiness of the content they encounter.

The ultimate goal is to advance fake news detection by creating a hybrid CNN-BERT model that successfully detects fake news articles with high accuracy and robustness. The proposed research aims to advance the state-of-the-art in fake news detection methods and to offer insightful information to academics, professionals, and policymakers who are involved in the fight against misinformation.

1.4 OBJECTIVE

The objectives of the proposed work on fake news detection are as follows:

- Develop a comprehensive dataset: Create a well-annotated dataset consisting of labeled examples of fake news and genuine news articles. This dataset will serve as the foundation for training and evaluating the models.
- Preprocess and encode textual data: Preprocess the textual data by applying techniques such as tokenization, stemming, and removing stop words. Convert the preprocessed text into numerical representations that can be processed by the models.
- Fine-tune Roberta for fake news detection: Train and fine-tune the Roberta model using the labeled dataset to enhance its ability to identify linguistic features and patterns associated with fake news. Adjust the model's parameters and optimize it for improved performance.
- Adapt RegNet for textual data: Repurpose the RegNet model originally designed for image recognition to process textual inputs. Develop a text-to-image encoding mechanism to convert the textual features into visual representations that RegNet can analyze.
- Combine Roberta and RegNet in an ensemble model: Integrate the fine-tuned Roberta model and the adapted RegNet model into a hybrid ensemble model. Design a fusion mechanism that effectively combines the textual and visual representations to leverage the strengths of both models.
- Evaluate and validate the model: Assess the performance of the ensemble model using appropriate evaluation metrics such as accuracy, precision, recall, and F1 score. Validate the model's effectiveness in detecting fake news by comparing its predictions against the ground truth labels from the dataset.

Overall, the objective of the proposed work is to develop an advanced ensemble model that effectively combines the power of Roberta and RegNet for accurate and reliable fake news detection. The aim is to provide a valuable tool to combat misinformation and promote a more informed and trustworthy information ecosystem.

2. LITERATURE SURVEY

2.1 Survey of Existing Model/Work

Predicting image credibility in fake news over social media using multi-modal approach

In the paper, Bhuvanesh Singh and, Dilip Kumar Sharma propose an efficient multi-modal approach, which detects fake images of microblogging platforms. The proposed framework utilizes the explicit convolution neural network model EfficientNetB0 for images and sentence transformer for text analysis. The feature embedding from visual and text is passed through dense layers and later fused to predict fake images. The proposed model is tested on a publicly available microblogging dataset, MediaEval (Twitter) and Weibo, to validate its effectiveness. In the proposed model, the visual and textual modalities are learned on respective channels and later fused to get the feature sets from both modalities. There are no additional components required for understanding the correlation between modalities.

MRDCA: a multimodal approach for fine-grained fake news detection through integration of RoBERTa and DenseNet based upon fusion mechanism of co-attention

In the paper, the authors Lingfei Qian, Ruipeng Xu and, Zhipeng Zhou proposed a multimodal approach integrating RoBERTa with DenseNet through a fusion mechanism of co-attention (MRDCA). RoBERTa was employed for extracting text features, and DenseNet was employed for extracting image features. The co-attention mechanism had the advantage of dynamically learning and capturing information interaction between text and image modal features. Experimental results demonstrated that the MRDCA per- formed better in identifying manipulated content, false connection and truth than in identifying imposter content, misleading content and satire/parody.

Multimodal fake news detection via progressive fusion networks

Authors Jing Jing, Hongchen Wu [*], Jie Sun, Xiaochang Fang and Huaxiang Zhang proposed a progressive fusion network (MPFN) for multimodal disinformation detection, which captures the representational information of each modality at different levels and achieves fusion between modalities at the same level and at different levels by means of a mixer to establish a strong connection between the modalities. Specifically, they used a transformer structure, which is effective in computer vision tasks, as a visual feature extractor to gradually sample features at different levels and combine features obtained from a text feature extractor and image frequency domain information at different levels for fine-grained modelling. In addition, they designed a feature fusion approach to better establish connections between modalities, which can further improve the performance and thus surpass other network structures in the literature. Extensive experiments were conducted on two real datasets, Weibo and Twitter

SpotFake: A Multi-modal Framework for Fake News Detection

In this paper, the authors Shivangi Singhal, Rajiv Ratn Shah, Tanmoy Chakraborty etc proposed architecture that aims to detect whether a given news article is real or fake. It does not take into account any other sub-task in the detection process. The prime novelty of SpotFake is to incorporate the power of language models, i.e. Bidirectional Encoder Representations from Transformers (BERT) to incorporate contextual information. The image features are learned from VGG-19 pre-trained on the ImageNet dataset. The representations from both modalities are then concatenated together to produce the desired news vector. This news vector is finally used for classification.

Detecting fake news with capsule neural networks

In this paper, the authors Mohammad Hadi Goldani, Saeedeh Momtazi and Reza Safabakhsh proposed to use of capsule neural networks in the fake news detection task. they used different embedding models for news items of different lengths. Static word embedding was used for short news items, whereas non-static word embeddings that allow incremental up-training and updating in the training phase were used for medium-length or long news statements. Moreover, they applied different levels of n-grams for feature extraction. The proposed models were evaluated on two recent well-known datasets in the field, namely ISOT and LIAR. The results show encouraging performance, outperforming the state-of-the-art methods by 7.8% on ISOT and 3.1% on the validation set, and 1% on the test set of the LIAR dataset.

An Integrated Multi-Task Model for Fake News Detection

In this paper the authors proposed a novel fake news detection multi-task learning (FDML) model based on the following observations: 1) some certain topics have higher percentages of fake news, and 2) some certain news authors have higher intentions to publish fake news. The FDML model investigates the impact of topic labels for fake news and introduces contextual information of news at the same time to boost the detection performance on short fake news. Specifically, the FDML model consists of representation learning and multi-task learning parts to train the fake news detection task and the news topic classification task, simultaneously. The experiment results show that the FDML model outperforms state-of-the-art methods on real-world fake news datasets.

Multimodal Fake News Detection via CLIP-Guided Learning

This paper proposes an FND-CLIP framework, i.e., a multimodal Fake News Detection network based on Contrastive Language-Image Pretraining (CLIP). Given a piece of targeted multimodal news, they extracted the deep representations from the image and text using a ResNet-based encoder, a BERT-based encoder and two pair-wise CLIP encoders. The multimodal feature is a concatenation of the CLIP-generated features weighted by the standardized cross-modal similarity of the two modalities. The extracted features were further processed for redundancy reduction before feeding them into the final classifier. They also introduce a modality-wise attention module to adaptively reweight and aggregate the features. Extensive experiments were conducted on typical fake news datasets. The results indicated that the proposed framework has a better capability in mining crucial features for fake news detection. The proposed FND-CLIP can achieve better performances than previous works, i.e., 0.7%, 6.8% and 1.3%improvements in overall accuracy on Weibo, Politifact and Gossipcop, respectively. Besides, they justify that CLIP-based learning can allow better flexibility in multimodal feature selection.

An image and text-based multimodal model for detecting fake news in OSN s

This paper proposes a framework that flags fake posts with Visual data embedded with text. The proposed framework works on data derived from the Fakeddit dataset, with over 1 million samples containing text, image, metadata, and comments data gathered from a wide range of sources, and tries to exploit the unique features of fake and legitimate images. The proposed framework has different architectures to learn visual and linguistic models from the post individually. Image polarity datasets, derived from Flickr, are also considered for analysis, and the features extracted from these visual and text-based data helped in flagging news. An ensemble model was designed to improve the identification of fake news with the Xception model to help in identifying images with high digital alterations, BERT to learn contextual knowledge and Visual sentiment analysis to learn features that distinguish an image with negative sentiment from that which induces positive emotions, thereby identifying misleading and tampered fake images with high confidence.

An ensemble machine learning approach through effective feature extraction to classify fake news

In this paper, the authors proposed an ensemble classification model for detection of the fake news that has achieved a better accuracy compared to the state-of-the-art. The proposed model extracts important features from the fake news datasets, and the extracted features are then classified using the ensemble model comprising of three popular machine learning models namely, Decision Tree, Random Forest and Extra Tree Classifier. We achieved a training and testing accuracy of 99.8% and 44.15% respectively on the ISOT dataset. For the Liar dataset, we achieved a training and testing accuracy of 100%.

2.2 Summary Gaps identified in the survey.

Most research work in this area is not based on the user's input but solely focused on the accuracy of the models. The literature review doesn't go into great detail on the evaluation measures each study utilised. Knowing the precise performance metrics (such accuracy, precision, recall, and F1-score) employed to assess the suggested models and how they stack up against current methodologies would be useful. These details would shed light on the robustness and efficacy of the suggested strategies.

Comparison with State-of-the-Art: While some studies mention state-of-the-art methods in passing, there is a dearth of in-depth comparisons with currently used methods in the field. A thorough evaluation and comparison of the suggested models with other cutting-edge approaches, highlighting their benefits and drawbacks, would be beneficial.

The literature review suggests using a variety of datasets for evaluation, including MediaEval, Weibo, Twitter, ISOT, LIAR, and others. The number, properties, and diversity of these datasets are all poorly understood, though. Readers would better grasp the generalizability and applicability of the suggested models if more information about the datasets used was provided.

Analysis of False Positives and Negatives: A discussion of false positives and false negatives in the findings section would be helpful. The kinds of misclassifications the suggested models make can help us understand their shortcomings and possible areas for development

Comparison of Modalities: Despite the fact that the studies combine textual and visual elements, there is no discussion of the relative value or contribution of each modality to the results as a whole. Understanding of the suggested models might be improved by providing a comparative study of the separate contributions of visual and textual characteristics.

The literature review largely focuses on how the suggested models perform on particular datasets, like the Weibo, Twitter, and false news datasets. The generalizability of the models to various systems, languages, or domains, however, is not sufficiently discussed. It is crucial to evaluate the generalizability of the suggested models outside the datasets utilised in the studies given the variety of social media platforms and news sources. We couldn’t find any paper which had the objective to create a UI or a prototype for FND.

3. OVERVIEW OF THE PROPOSED SYSTEM

3.1 Introduction and Related Concepts

The proposed system uses the following cocepts to incorporate the following:

Fake News: Fake news refers to deliberately false or misleading information presented as factual news. It is created with the intention to deceive or manipulate readers, often spreading rapidly through social media platforms and other online channels. Fake news can have significant consequences, including the distortion of public opinion, erosion of trust, and impact on democratic processes.

Natural Language Processing (NLP): Natural Language Processing is a branch of artificial intelligence that focuses on the interaction between computers and human language. It involves the development of algorithms and models to understand, interpret, and generate human language. NLP techniques are crucial for tasks such as text classification, sentiment analysis, and language understanding, making them relevant for fake news detection.

Masked Language Modeling (MLM): It is a technique used in NLP to predict missing or masked words in a sentence. The goal is to train the model to understand the relationships between words and to learn the statistical patterns of language. The model is trained on a large corpus of text data to learn grammar, syntax, and semantic relationships between words.

Self-attention mechanisms: Also known as transformer models, are a fundamental component of modern deep learning architectures. They allow models to capture relationships between different elements within a sequence of data, such as words in a sentence or frames in a video, without relying on recurrent or convolutional operations. To calculate attention scores, a dot product is performed between the query vector of a given element and the key vectors of all other elements in the sequence. The value vectors of all elements are weighted by their corresponding attention weights and summed up to obtain the attended representation of the current element.

RoBERTa model: RoBERTa is a state-of-the-art language model based on the transformer architecture. It was developed by Facebook AI Research and has achieved superior performance on a wide range of NLP tasks. It has a similar architecture to BERT, consisting of a stack of transformer layers and self-attention mechanisms. It has been pre-trained on a large corpus of unlabeled text data and can be fine-tuned on specific downstream tasks with relatively small amounts of labeled data.

RegNet: RegNet is a family of neural network architectures designed to achieve high efficiency and scalability. It was introduced by Facebook AI Research to address the challenges of training deep neural networks with a large number of parameters. RegNet models are built using a Residual Group, which contains convolutional layers and skip connections. The scaling factors (depth, width, and resolution) are carefully chosen based on predefined design rules to ensure efficient resource utilization and maximize performance. RegNet models are particularly useful in resource-constrained scenarios.

Transformers: Transformers are a type of deep learning architecture that rely on self-attention mechanisms to capture relationships and dependencies between different elements in a sequence. They consist of an encoder and decoder, and are based on a stack of identical layers containing two sub-layers: a multi-head self-attention mechanism and a position-wise fully connected feed-forward network. They have revolutionized NLP by capturing long-range dependencies and achieving superior performance on a variety of tasks.

3.2 Framework, Architecture or Module for the Proposed System

The following section describes our multimodal approach to detecting false news. The architecture of our proposed model is depicted in Figure 2. The model has four components. The first section is the textual feature extractor, extracting contextual text features using RoBERTa and CNN layers. The second component of the model is the visual feature extractor, which removes the optical characteristics of an image from a post. In the third section, the joint feature extractor, we proposed an attention mechanism to extract features from both text and pictures. The final component is a multiple-feature combination component that combines the representations derived from various parts to produce the feature representation for the entire post.

We evaluated our proposed model on MediaEval 2016 data. The dataset was made available to the public for the Verifying Multimedia Use challenge at MediaEval 2016. The challenge is to distinguish between true and false information. The dataset includes tweets and images associated with events. The training set consists of 9,000 tweets with false news and 6,000 tweets with genuine news, while the test set contains 2,000 tweets with news. Some messages include videos, but we retained the data with text and images and excluded the samples.

Textual feature Extractor:

We preprocessed texts before extracting features. We shortened words and tokens. “Coooool” becomes “Cool”.Text-based emoticons include ":)", ":(", etc. "Happy" and "Sad" replaced those emoticons. We used ekphrasis to tokenize, normalise, and segment words. RoBERTa, the state-of-the-art model in many NLP applications, extracts a tweet's feature representation to capture semantic and contextual information best. RoBERTa model excels in text categorization and other NLP tasks. The final four buried levels are token contextual embeddings. After that, we forecast using DCNN layers with filter sizes 2, 3, 4, and 5. After sending the embedding vectors through DCNN layers, we stack those outputs vertically and pass through two further 1D-CNN layers with residual connections to get the output. Finally, we flatten Tm, send it through two completely linked layers, and get the vector size of the textual representation Tf, dT = 32.

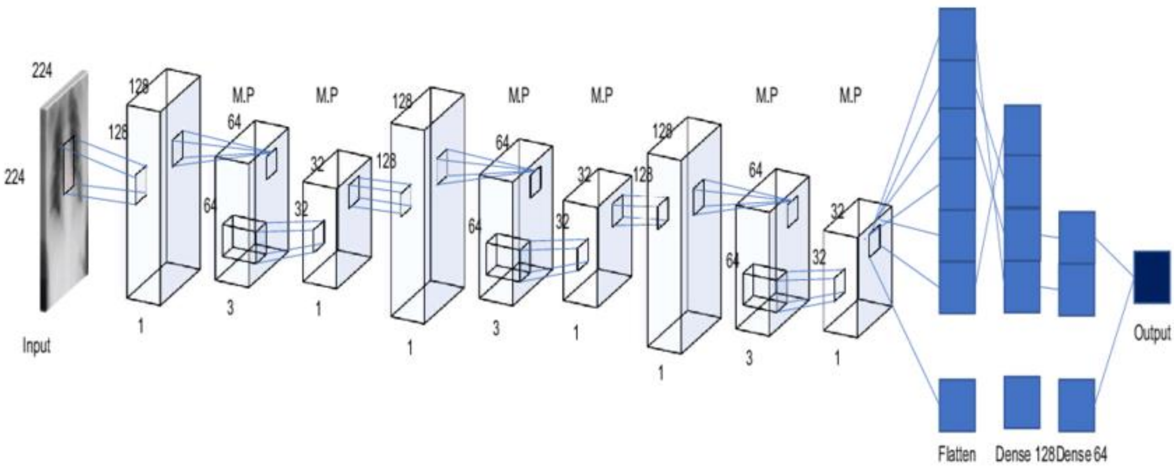
Visual Feature Extractor:

We use a Regnet model trained on the ImageNet dataset [21] to extract visual features. We extract the output of the second-to-last layer of Regnet and pass it through two fully connected layers to reduce the dimension to a vector size of dI = 32 as the final visual representation if the condition holds. In addition, we extract the output of the third-to-last layer, Im, which will be used later in the common feature extraction section. Im is transformed from a 3D tensor to a 2D tensor with the shape regionsdIm, where regions is the number of pixels in the output of Regnet's second-to-last layer. 7*7 = 49 regions make up an image of size 224*224. Finally, we place it in an entirely connected layer and obtain the 32-pixel-wide visual feature representation.

3.3 Proposed System Model(ER Diagram/UML Diagram/Mathematical Modeling)

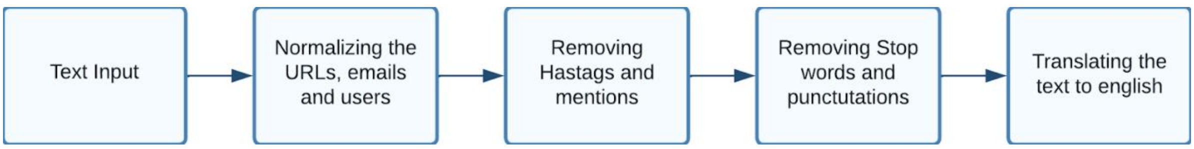
System Architecture:

Regnet:



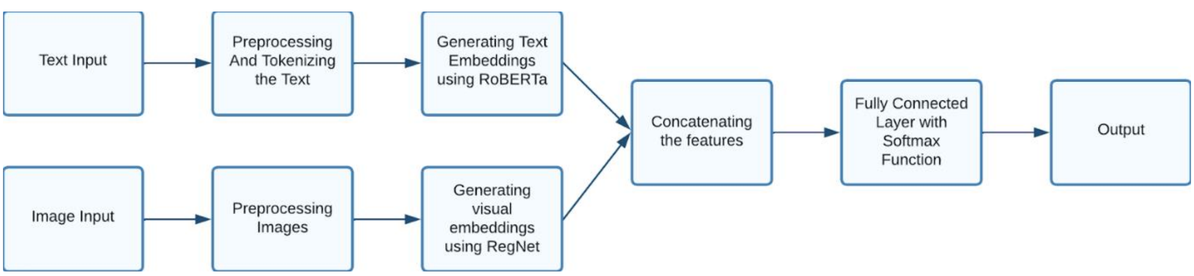
System Model:

Preprocessing the Texts:



Preprocessing the Images

Architecture:



4. PROPOSED SYSTEM ANALYSIS AND DESIGN

4.1 INTRODUCTION

The proposed system aims to address the pressing issue of fake news by leveraging the capabilities of Roberta and RegNet, two powerful models from the fields of natural language processing (NLP) and image recognition. Fake news has become a significant societal challenge, with the potential to manipulate public opinion, spread misinformation, and undermine trust in media sources. To combat this problem, an advanced solution is required that can effectively detect and classify fake news from genuine news articles or textual content.

The proposed system combines the strengths of models to create a comprehensive framework for fake news detection. One, based on the transformer architecture, excels in understanding the contextual nuances of text, capturing linguistic patterns, and discerning semantic cues. By fine-tuning Roberta on labeled datasets specifically curated for fake news detection, it can be trained to identify linguistic features indicative of misinformation.

Second one, originally designed for image recognition, is adapted to process textual inputs by converting them into visual representations. This allows for the analysis of visual patterns, irregularities, and suspicious cues in the text, which can complement the linguistic analysis performed by Roberta. By treating text as images, RegNet's convolutional neural networks can detect visual inconsistencies and uncover hidden patterns that may not be evident through linguistic analysis alone.

The proposed system's hybrid ensemble model combines the output, incorporating both textual and visual representations for a more comprehensive analysis of news content. By leveraging the deep contextual understanding of Roberta and the visual analysis capabilities of RegNet, the system aims to enhance the accuracy of fake news detection by capturing a wider range of features and signals.

4.2 Requirement Analysis

4.2.1 Functional Requirements

4.2.1.1 Product Perspective

From a product perspective, the proposed system for fake news detection can be seen as an advanced technological tool aimed at addressing the challenges posed by the proliferation of misinformation. It is designed to provide an automated solution for detecting and classifying fake news, enhancing the ability of individuals, news organizations, and social media platforms to identify and filter out misleading information. The system operates as a software application or service that takes in textual content, such as news articles or social media posts, as input. It leverages the power of newer and complex models, which have been trained and fine-tuned on labeled datasets, to analyze and assess the authenticity of the provided text.

The product offers several key features and functionalities. Firstly, it employs the linguistic analysis capabilities to capture linguistic patterns, semantic cues, and sentiment associated with fake news. This allows it to detect instances where language is used to manipulate or mislead readers. Secondly, the system utilize adaptation for textual data to extract visual representations from the text. By treating text as images, it applies convolutional neural networks to identify visual patterns, irregularities, and inconsistencies that may indicate the presence of fake news.

The system can be integrated into various platforms and applications, including social media platforms, news aggregator websites, or content moderation systems. It can serve as an additional layer of defense against the spread of misinformation, helping users make informed decisions about the credibility of the information they encounter.

Overall, the proposed system offers an advanced technological solution to combat fake news, providing a valuable tool for detecting and filtering out misinformation. It empowers users and platforms to foster a more informed and reliable information ecosystem, ensuring the dissemination of accurate and trustworthy content.

4.2.1.2 Product Features:

The proposed system for fake news detection incorporates several key features to effectively identify and classify fake news:

- Textual Analysis: The system utilizes Roberta's linguistic analysis capabilities to examine the text for linguistic patterns, semantic cues, sentiment, and other linguistic features associated with fake news. It captures subtle linguistic nuances that may indicate misleading or fabricated information.
- Visual Analysis: The system employs RegNet, adapted for textual data, to extract visual representations from the text. By treating text as images, it applies convolutional neural networks to detect visual patterns, irregularities, and inconsistencies that may reveal hidden signals of fake news.
- Hybrid Ensemble Model: The system combines the outputs of both in a hybrid ensemble model. This fusion of linguistic and visual analysis enhances the overall accuracy and reliability of fake news detection, capturing a broader range of features and signals.
- Scalability and Efficiency: The system is designed to be scalable and efficient, capable of processing large volumes of textual content in a timely manner. It leverages the parallel processing capabilities of modern hardware to ensure efficient and fast analysis.

These features collectively make the proposed system a powerful tool for identifying and classifying fake news, aiding in the fight against misinformation and promoting the dissemination of accurate and reliable information.

4.2.1.3 User Characteristics

The user characteristics for the following system are as follows:

- General Users: The system can be utilized by general users who consume news and information online. It empowers them to verify the credibility of the content they encounter, enabling more informed decision-making and reducing the risk of being misled by fake news.
- Social Media Users: Social media platforms have become a primary source of news for many individuals. The system can be integrated into social media platforms, allowing users to verify the authenticity of news articles or posts before sharing them with their networks.
- News Organizations: News organizations can benefit from the system by using it as an additional layer of fact-checking and verification. It can help journalists and editors identify potential fake news articles, ensuring that only accurate and trustworthy information is published.
- Content Moderation Teams: Online platforms and forums often employ content moderation teams to monitor and filter user-generated content. The system can be integrated into these moderation workflows, assisting moderators in identifying and removing fake news content more effectively.
- Researchers and Academics: The proposed system can be utilized by researchers and academics who study misinformation and fake news. It provides them with a valuable tool for analyzing the prevalence and characteristics of fake news, aiding in the development of strategies to combat its spread.

It is essential to note that while the proposed system caters to a diverse set of user characteristics, it may require varying levels of technical expertise and access privileges based on the specific implementation and integration requirements. The system aims to provide a user-friendly experience, regardless of the user's technical background or domain expertise, making fake news detection accessible and beneficial to a broad range of users.

4.2.1.4 Assumptions and Dependencies:

Assumptions:

- Labeled Dataset Availability: The proposed system assumes the availability of a well-annotated dataset consisting of labeled examples of fake news and genuine news articles. This dataset is essential for training and evaluating the models. It is assumed that a reliable and representative dataset can be obtained or created for this purpose.
- Training Data Representativeness: The effectiveness of the proposed system depends on the training data being representative of the real-world distribution of fake news. It assumes that the labeled dataset captures a wide range of fake news instances, including various types, styles, and linguistic patterns commonly observed in misinformation.
- Model Generalization: The system assumes that the fine-tuned models which can generalize well beyond the training data. It assumes that the models can effectively capture and learn the features and patterns associated with fake news, enabling them to make accurate predictions on unseen data.

Dependencies:

- Availability of Computational Resources: The proposed system relies on computational resources, such as hardware and software, to train, fine-tune, and deploy models.
- Integration with Existing Systems: To fully utilize the system's capabilities, integration with existing platforms, applications, or content moderation systems may be required. This dependency relies on the availability of appropriate integration options, such as APIs or SDKs, and cooperation from the relevant platform or system providers.

It is important to consider these assumptions and dependencies when implementing and evaluating the proposed system, as they can impact its performance, scalability, and overall effectiveness in detecting fake news.

4.2.1.5 Domain Requirements:

Domain Requirements for Fake News Detection:

- Reliable and Diverse Dataset: The system requires a reliable, diverse, and well-labeled dataset of fake news and genuine news articles for training and validation purposes. The dataset should encompass various types of fake news and represent the real-world distribution of misinformation.
- High Accuracy and Precision: The system should exhibit high accuracy and precision in detecting fake news. It should minimize false positives (misclassifying genuine news as fake) and false negatives (failing to identify actual instances of fake news), ensuring reliable and trustworthy results.
- Scalability and Efficiency: The system should be scalable and efficient, capable of processing large volumes of textual data in a timely manner. It should leverage optimized algorithms and computational resources to handle increasing workloads and deliver fast and responsive fake news detection.
- Seamless Integration and Compatibility: The system should offer integration options, such as APIs or SDKs, to facilitate easy integration with existing platforms, applications, or content moderation systems. It should be compatible with different environments and workflows, enabling smooth incorporation of fake news detection capabilities.
- User-Friendly Interface and Interpretability: The system should provide a user-friendly interface that is intuitive and accessible to users with varying technical backgrounds. It should present clear and interpretable results, showcasing the linguistic and visual cues contributing to the detection of fake news, enhancing user understanding and trust in the system.

By addressing these domain requirements, the proposed system can effectively detect and classify fake news, support user needs, and contribute to combating the spread of misinformation.

4.2.1.6 User Requirements:

User requirements for the proposed system for fake news detection can be summarized as follows:

- Accuracy and Reliability: Users expect the system to accurately detect and classify fake news, minimizing both false positives and false negatives. They require a reliable solution that can effectively identify misinformation, allowing them to make informed decisions about the credibility of the content they encounter.
- Easy Integration and Seamless Workflow: Users desire a system that can seamlessly integrate into their existing platforms, applications, or content moderation systems. They expect integration options such as APIs or SDKs that simplify the incorporation of the fake news detection capabilities into their workflows, ensuring a smooth and efficient user experience.
- User-Friendly Interface: Users require a user-friendly interface that is intuitive and accessible, regardless of their technical background. They expect a straightforward and easy-to-use interface that allows them to input text or upload articles for analysis and provides clear and understandable results.
- Interpretability and Explanations: Users value interpretability and explanations from the system. They want insights into the linguistic and visual cues that led to the classification of a piece of content as fake news. Users seek transparency and understanding of the factors considered by the system, enabling them to comprehend and trust the system's classifications.

By fulfilling these user requirements, the proposed system can meet the expectations of users by providing accurate, easy-to-use, and interpretable fake news detection capabilities that integrate seamlessly into their existing workflows while continuously improving to address emerging challenges in the fight against misinformation.

4.2.2 NON – FUNCTIONAL REQUIREMENTS

4.2.2.1 Product Requirements

- High Accuracy Fake News Detection: The system should achieve a high level of accuracy in detecting fake news, with a minimum accuracy rate specified, to provide reliable and trustworthy results to users.
- Seamless Integration: The system should offer seamless integration options, such as well-documented APIs or SDKs, allowing easy incorporation of fake news detection capabilities into existing platforms, applications, or content moderation systems.
- User-Friendly Interface: The system should feature a user-friendly interface that is intuitive, visually appealing, and easy to navigate. Users should be able to input text or upload articles effortlessly, with clear instructions and visually understandable results displayed.
- Interpretability and Explanations: The system should provide interpretability and explanations for its fake news detection results, highlighting the key linguistic and visual cues considered. It should offer transparency and insights into the decision-making process, helping users understand why content is classified as fake news.
- Continuous Improvement Mechanism: The system should support continuous improvement and adaptation to evolving fake news trends. It should facilitate regular updates, model enhancements, and refinements based on feedback and emerging research, ensuring its effectiveness in detecting new forms of fake news.

By fulfilling these product requirements, the proposed system can provide accurate, integrated, user-friendly, interpretable, and continuously improved fake news detection capabilities that enhance user experience and contribute to combating misinformation.

4.2.2.1.1 Efficiency

The Efficiency is an important aspect of the proposed system for fake news detection.The following efficiency requirements can be considered:

- Processing Speed: The system should demonstrate efficient processing speed, allowing it to analyze and classify textual data in a timely manner. It should leverage optimized algorithms, parallel processing techniques, and efficient hardware utilization to minimize processing time and provide quick results
- Scalability: The system should be designed to scale effectively with increasing workloads. It should be able to handle large volumes of textual data without compromising performance. This scalability ensures that the system can accommodate growing demands and maintain its efficiency even as the workload increases.
- Resource Optimization: The system should optimize the utilization of computational resources, such as CPU and memory, to minimize resource consumption while maximizing performance. It should leverage efficient data structures, caching mechanisms, and memory management techniques to ensure efficient utilization of available resources.
- Batch Processing Capabilities: The system should support batch processing capabilities, allowing users to submit multiple texts or articles for analysis simultaneously. This feature enhances efficiency by enabling the system to process multiple inputs in parallel, reducing overall processing time and enhancing throughput.

Efficiency is crucial to provide timely and accurate fake news detection, enabling users to make informed decisions quickly. By meeting these efficiency requirements, the proposed system can effectively process and classify textual data while optimizing resource utilization and minimizing errors, resulting in an efficient and reliable fake news detection solution.

4.2.2.1.2 Reliability

The Reliability is a critical aspect of the proposed system for fake news detection.The following reliability requirements should be considered:

- Accuracy and Consistency: The system should demonstrate a high level of accuracy in detecting fake news, minimizing false positives and false negatives. It should consistently provide reliable results that users can trust when evaluating the credibility of the content they encounter.
- Robustness to Variability: The system should be robust to variations in the types, styles, and linguistic patterns of fake news. It should perform reliably across a diverse range of fake news instances, ensuring consistent detection capabilities regardless of the specific characteristics or techniques employed in the misinformation.
- Generalization Capability: The system should exhibit the ability to generalize well beyond the training data. It should be reliable in classifying fake news articles that differ from the examples seen during training, capturing and understanding the underlying features and patterns associated with misinformation effectively.
- Performance under Workload: The system should maintain its reliability and accuracy even under varying workloads. It should handle increasing volumes of textual data without compromising its detection capabilities, ensuring consistent and reliable results even during peak usage periods.
- Data Integrity and Security: The system should ensure the integrity and security of user data throughout the fake news detection process. It should protect against data corruption, unauthorized access, and potential tampering, adhering to data privacy regulations and implementing robust security measures.

Reliability is essential to build user trust and confidence in the system's fake news detection capabilities. By meeting these reliability requirements, the proposed system can provide accurate and consistent results, handle varying workloads, ensure data integrity, and continuously improve its performance and effectiveness in detecting fake news.

4.2.2.1.3 Portability

The following portability requirements should be considered:

- Platform Compatibility: The system should be designed to be compatible with multiple platforms and operating systems. It should be able to run seamlessly on different environments, such as Windows, macOS, Linux, or cloud-based platforms, ensuring broad accessibility and ease of deployment.
- Hardware Independence: The system should be hardware-independent, allowing it to run on a variety of hardware configurations without significant modifications. It should leverage efficient resource utilization and be adaptable to different computational environments, ranging from low-end devices to high-performance servers.
- Deployment Flexibility: The system should provide flexibility in deployment options, allowing users to choose between on-premises installations or cloud-based deployments. It should support containerization technologies like Docker to simplify deployment processes and enable easy deployment across different environments.
- API-based Integration: The system should offer well-documented APIs that enable seamless integration with other systems and applications. It should provide clear guidelines and documentation for developers to interact with the system programmatically, facilitating integration into existing software infrastructure.

By meeting these portability requirements, the proposed system can be easily deployed and integrated into different environments and platforms. It ensures accessibility, flexibility, and compatibility, allowing users to leverage the fake news detection capabilities across various systems and adapt to their specific deployment requirements and preferences..

4.2.2.1.4 Usability

Usability is a crucial aspect of the proposed system and these are the following usability requirements should be considered:

- Intuitive User Interface: The system should feature an intuitive user interface that is easy to navigate and understand. It should have clear and logically organized menus, buttons, and input fields, allowing users to interact with the system effortlessly.
- User Guidance and Feedback: The system should provide clear instructions and guidance to users on how to use the system effectively. It should offer informative messages, tooltips, or contextual help to assist users in understanding the system's features and functionality. Additionally, the system should provide feedback to users during processing to keep them informed about the progress and status of their requests.
- Easy Input Methods: The system should support various input methods, such as text input, file upload, or web scraping, making it convenient for users to submit articles or textual data for analysis. It should handle different data formats and provide clear instructions on the supported input methods.
- Visual Representations: The system should present the results in a visually understandable format, utilizing charts, graphs, or visual indicators to convey information effectively. Visual representations can aid users in quickly interpreting the fake news detection results without requiring extensive text analysis.
- Customization and Preferences: The system should allow users to customize certain aspects according to their preferences. This may include options for adjusting sensitivity thresholds, selecting specific analysis parameters, or customizing the display settings. By offering customization options, the system can cater to individual user preferences and improve overall usability.

By meeting these usability requirements, the proposed system can offer an intuitive, user-friendly experience, ensuring that users can easily interact with the system, understand the results, and make informed decisions regarding the credibility of news articles.

4.2.2.2 Organisational Requirements

4.2.2.2.1 Implementation Requirements

To implement this project, the key requirements are:

•Computing infrastructure: The neural network model requires GPUs and potentially significant compute power to train and generate sequences effectively. For casual or small-scale use, a high-end consumer PC may suffice. For enterprise or commercial deployments, more robust compute infrastructure would be needed such as servers with high-end GPUs, access to cloud computing services, etc.

•Software dependencies: The project relies on several open-source libraries like Keras, TensorFlow, and Jupyter Notebooks. To run the model training and inference scripts, these dependencies would need to be installed and compatible versions ensured. For any systems that interact with the model, these same dependencies would likely be required.

•Data storage: Storage is required for the training data, neural network model files, and any generated outputs like MIDI files. The training data is included in the GitHub repository and the model is less than 100MB, so overall storage needs are quite modest. But at large scales, data could accumulate rapidly.

•Programming and ML skills: To understand, use, modify or recreate this project, skills in areas like Python programming, machine learning, Keras/TensorFlow, and music information retrieval would be very valuable. For any sizeable organization looking to leverage a system like this, access to technical skills and knowledge will be important.

•User experience design: To turn this project into a product, additional work around user experience design, interface development, and interaction flows would need to be done. Deploying an open-source prototype into a polished product or service is no trivial task and would require UX skills and knowledge.

4.2.2.2.2 Engineering standards Requirements

The AI system does not necessarily conform to rigorous engineering standards that would normally be required for a commercial product. However, there are certain standards and best practices that could be applied:

•Code quality: The Python scripts could adhere to style guidelines like PEP 8 and be thoroughly commented and documented. Unit and integration testing could be implemented. These measures improve code readability, reusability, and reliability.

•Data validation: The training data could go through additional validation to ensure it contains no biases or other issues before using to build a model for production use. Regular data evaluation processes could be put in place.

•Model evaluation: Metrics to assess the performance, accuracy, and reliability of the neural network model could be more formally defined and monitored over time. Thresholds for when re-training a model might be required could be established.

•Infrastructure security: For any sizeable deployment, IT security standards around user access, data protection, compute infrastructure, etc. would need to be implemented to avoid potential cyber risks.

•Software robustness: Additional testing, debugging, and hardening of any systems built around the AI Duet model would help minimize the chance of software bugs, vulnerabilities or downtime issues—especially for commercial use cases.

•Change management: A structured process for continued improvements, version control, updating dependencies, and tracking modifications could help in managing how this project and any related systems change over time. For enterprise use, a well-defined change management protocol is important.

•Documentation: More detailed documentation covering how the model works, its features and limitations, hardware and software requirements, and any other operational details could be provided for an organization looking to deploy this technology at scale. Thorough documentation is useful for both technical and non-technical stakeholders.

4.2.2.3 Operational Requirements

Economic: The project has minimal economic requirements. The only costs involved are the computational resources required to run the neural network model and generate the musical sequences. This cost is incurred by the providers of the project and any individuals who download and run the model on their local machines. For most casual users, the economic requirements are negligible. For large-scale or commercial use, the costs would increase significantly based on the volume of sequences generated and the infrastructure required.

Environmental: The environmental requirements and impact of this project are relatively low since it is a software-only system. The main environmental costs would come from the electricity required to power the servers and systems running the neural network model and generating the musical sequences. These costs would depend on the scale and volume of sequences generated. For most individual users, the environmental footprint would be minor. For large-scale deployment, the environmental requirements would be more substantial due to higher energy usage.

Social: The project has limited social requirements and impact. The project aims to generate musically pleasing sequences that can accompany a human musician, so the social outcome is enhancing the experience of those who interact with the system. However, the project could enable new forms of human-AI creative collaboration and even new genres of generative or interactive music involving both human musicians and AI systems. So, the potential long-term social impact could be quite significant if projects like this inspire new creative practices.

Political: There are few direct political requirements or implications of the project. However, some political issues could emerge if systems like this become widely used for commercial purposes or in ways that fundamentally impact how music is created or consumed. There may be policy debates around AI's role in the creative sector or concerns over AI making certain human jobs or skills obsolete. But for this specific open-source project, the political dimension is minimal.

Ethical: From an ethical perspective, the project should aim to generate musical sequences that are pleasant, harmless, and legally compliant. The training data and model should be evaluated to ensure no biased, unsafe or unlawful content can emerge from the system. Given the project's goal of providing an interactive experience for human musicians, it is important the system behaves ethically and supports a mutually enjoyable collaboration. However, an open-source system like this could potentially be misused for less ethical purposes, so ethical safeguards may need to be put in place if deployed at scale.

Health and Safety: There are no significant health and safety requirements for this project beyond the usual precautions around powering and operating computer systems. The software generates digital music files, so there are no physical materials, equipment or work environments to evaluate from a health and safety perspective. However, as with any AI system, health and safety issues may arise if the capabilities were misapplied for malicious use, but there is no evidence to suggest that is an issue for this particular open-source project.

Sustainability: The project is sustainable in the sense that as an open-source software project, it can continue to function for the foreseeable future at relatively little cost. However, the long term sustainability may depend on factors like: whether interest in the project remains and people continue using and enhancing the model; whether changes in technology infrastructure impact the system; how long the creators choose to maintain the project; whether commercial entities emerge to support more robust versions of the project, etc. So, while inherently sustainable as code and data, many social and business factors can influence the sustainability of any software project.

Legality: There do not appear to be any significant legal or compliance requirements for this project to operate. The software generates original musical sequences, so there are no apparent copyright or intellectual property issues. No protected data seems to be involved in the training or operation of the model. And the capabilities of the system do not enable any evident illegal behavior or activity. However, if this type of technology was used for commercial purposes or in ways that did enable unlawful behavior, legal issues may arise that would need to be addressed. But for an open-source project like this, there are few direct legality concerns.

Inspectability: The project is highly inspectable since all the source code and data involved in the neural network model will be available on GitHub. Anyone interested in the internals of how the system works can examine the code, evaluate the model architecture and hyper-parameters, analyze the training data, and replicate or build upon the work. So, this project fully satisfies any requirements around explainability, accountability, and transparency of AI systems. Of course, the model is still limited by the usual challenges of interpreting complex neural networks, but that is an issue for machine learning in general rather than any lack of inspectability in this project.

4.2.3 System Requirements

4.2.3.1 H/W Requirements

- UI/UX: The user interface (UI) for the Fake news detection is being developed on a Mac Book M1. The Mac Book M1 is a powerful machine with an 8-core CPU and an 8-core GPU, making it well-suited for running machine learning algorithms and developing user interfaces.
- GAN: The multimodal algorithm is being trained on a laptop with a 1060ti GPU and an i7 6500 CPU. The 1060ti is a popular graphics card for deep learning tasks and is well-suited for training Fake news detection. The i7 6500 is a quad-core CPU that is also capable of handling machine learning workloads.

4.2.3.2 S/W requirements

Fake news detection -

- Python: Python is a popular programming language for machine learning and deep learning. It will be used to implement the GAN algorithm, preprocess the data, and convert the generated notes into audio files.
- Tensorflow: These are popular deep learning frameworks that will be used to implement the multimodal algorithm.
- Hugging phase: These contain the transformer model that will be used in detecting the fake news.

UI/UX –

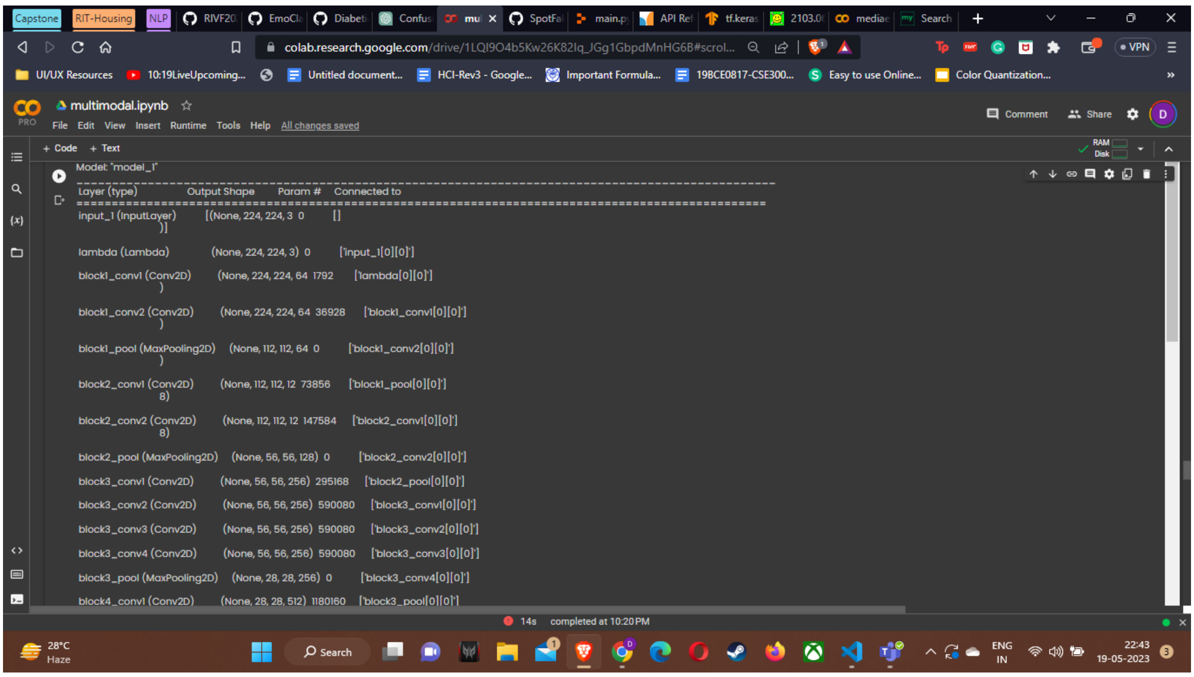
- HTML, CSS: HTML is a markup language used for creating the structure of web pages. It defines the different elements and their relationships to one another. CSS, on the other hand, is used for styling the HTML elements, such as setting the colors, fonts, and layout of the page. Together, HTML and CSS form the backbone of the user interface.

5. Results and Discussions

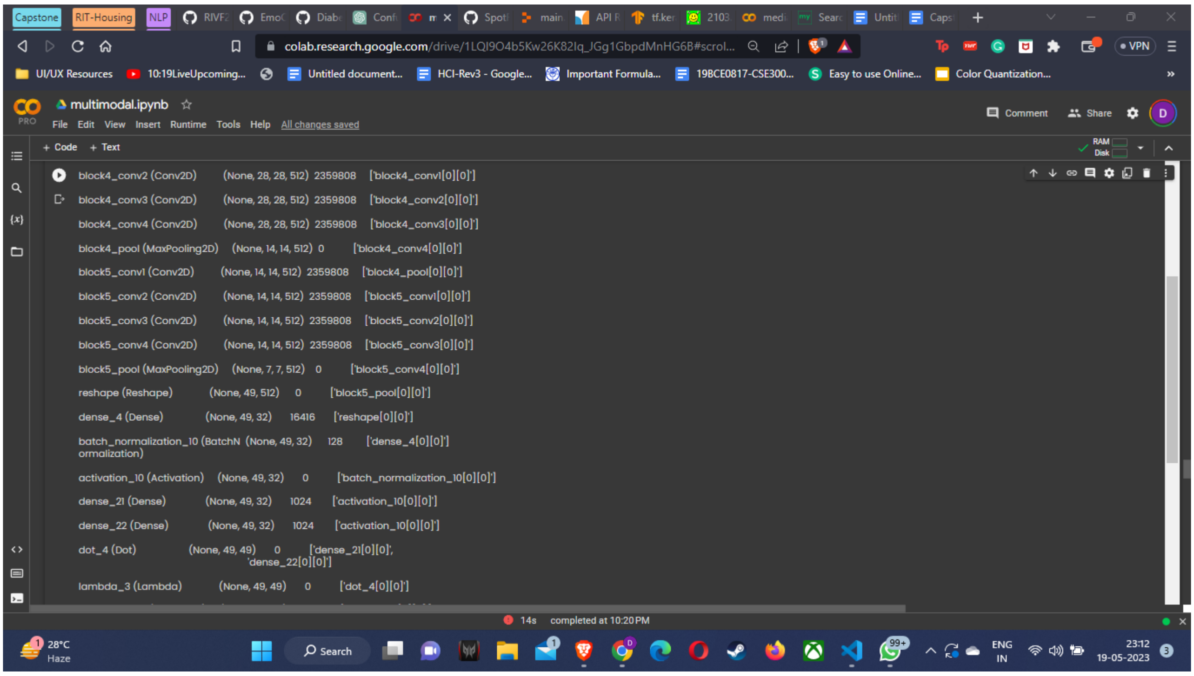
The basic working principle of the model is:

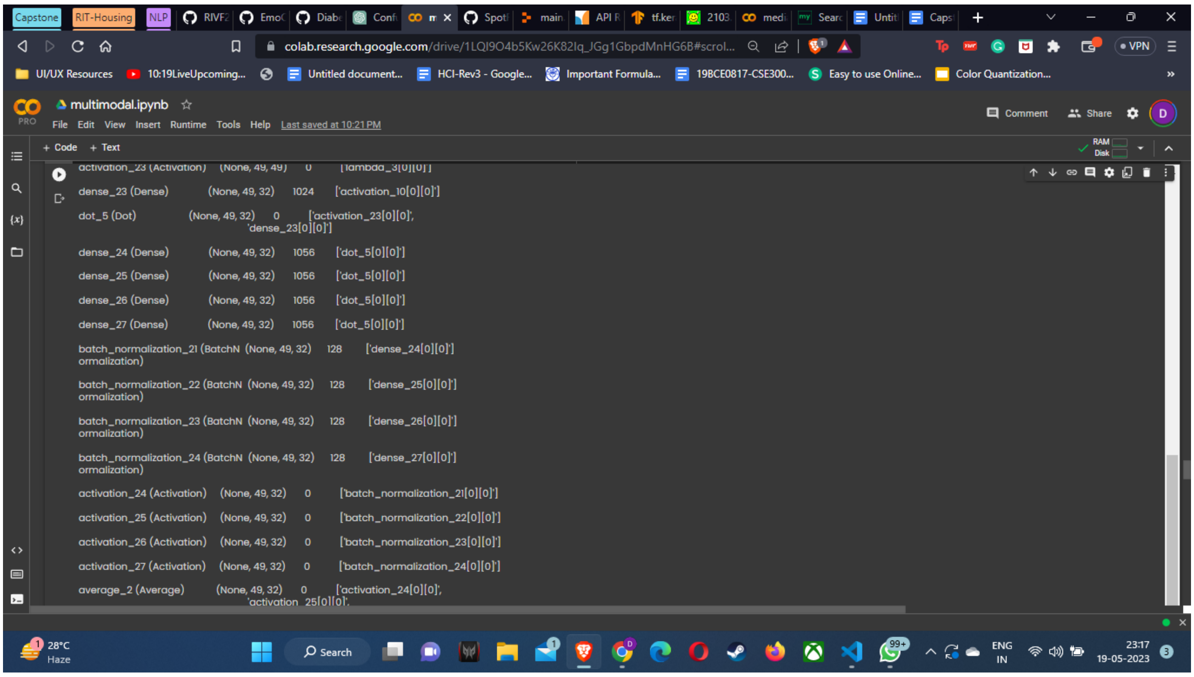
- The user inputs a tweet along with it's media files. The input is stored and analysed by the system.
- The system preprocesses the text and then translates it into English for further processing. The system then tokenises the text using the RoBERTa tokenizer and generates attention masks and input IDs. Then we use the RoBERTa model to create the text embeddings.
- The system preprocesses the image by resizing it and converting it to RGB form for further processing. Then the images are converted into NumPy arrays for further processing.
- Now the system uses CNN and RoBERTa architectures for extracting text embeddings and RegNet for extracting image embeddings.
- We then use the scaler self-attention mechanism to derive a relationship between the images and the text, and then we concatenate the image and text embeddings.
- After concatenation, we use a fully connected layer with softmax function as its activation function to make the predictions.T

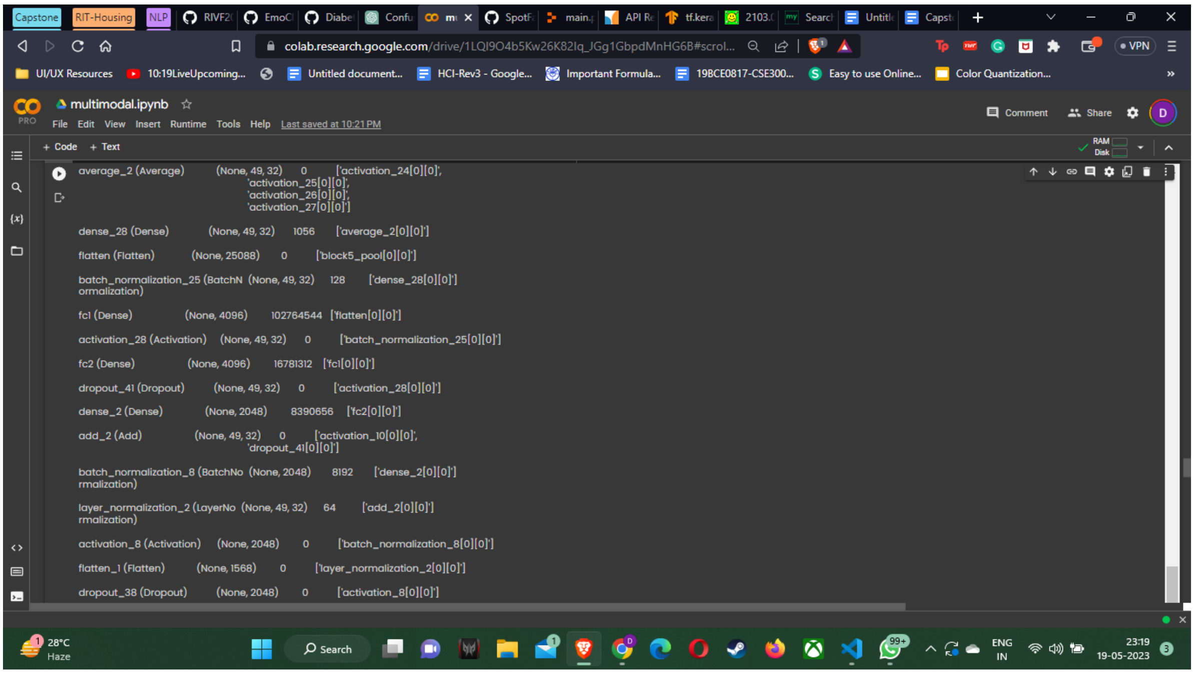
Multimodal Model Summary:

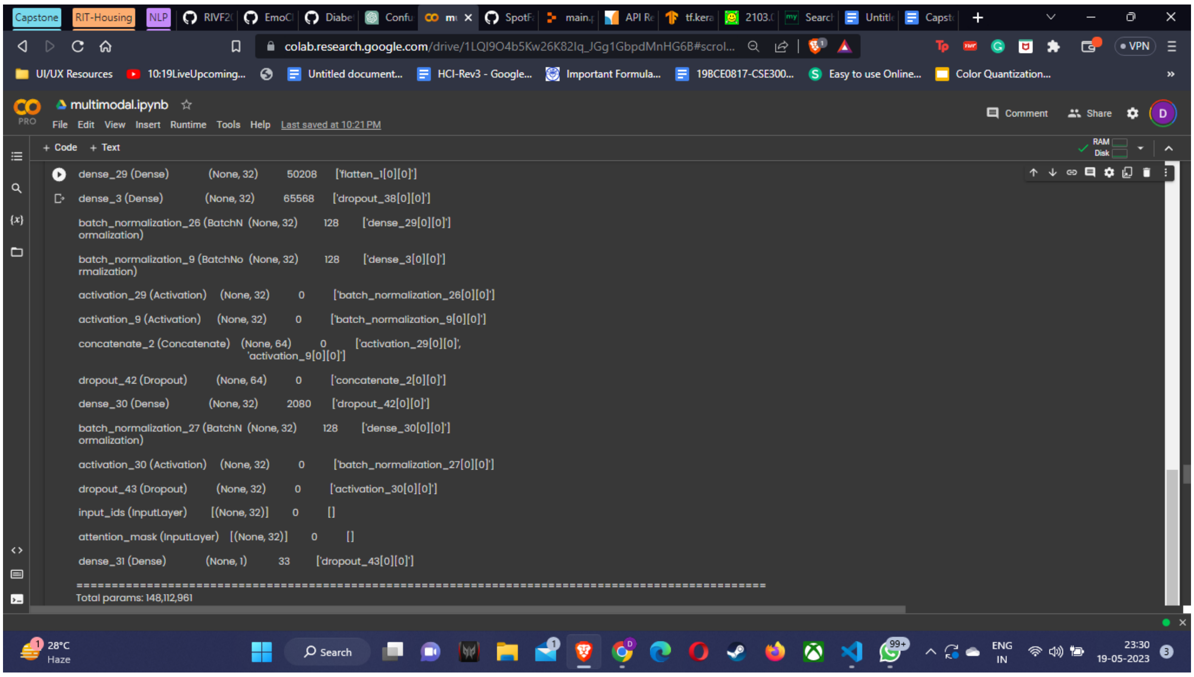


```
Model: "model_1"
________________________________________________________________________________
 Layer (type)              Output Shape      Param #   Connected to
================================================================================
 input_1 (InputLayer)      [(None, 224, 224, 3  0      []
                           )]
 lambda (Lambda)           (None, 224, 224, 3)  0      ['input_1[0][0]']
 block1_conv1 (Conv2D)     (None, 224, 224, 64  1792   ['lambda[0][0]']
                           )
 block1_conv2 (Conv2D)     (None, 224, 224, 64  36928  ['block1_conv1[0][0]']
                           )
 block1_pool (MaxPooling2D)  (None, 112, 112, 64  0    ['block1_conv2[0][0]']
                           )
 block2_conv1 (Conv2D)     (None, 112, 112, 12  73856  ['block1_pool[0][0]']
                           8)
 block2_conv2 (Conv2D)     (None, 112, 112, 12  147584  ['block2_conv1[0][0]']
                           8)
 block2_pool (MaxPooling2D)  (None, 56, 56, 128)  0    ['block2_conv2[0][0]']
 block3_conv1 (Conv2D)     (None, 56, 56, 256)  295168  ['block2_pool[0][0]']
 block3_conv2 (Conv2D)     (None, 56, 56, 256)  590080  ['block3_conv1[0][0]']
 block3_conv3 (Conv2D)     (None, 56, 56, 256)  590080  ['block3_conv2[0][0]']
 block3_conv4 (Conv2D)     (None, 56, 56, 256)  590080  ['block3_conv3[0][0]']
 block3_pool (MaxPooling2D)  (None, 28, 28, 256)  0    ['block3_conv4[0][0]']
 block4_conv1 (Conv2D)     (None, 28, 28, 512)  1180160  ['block3_pool[0][0]']
```

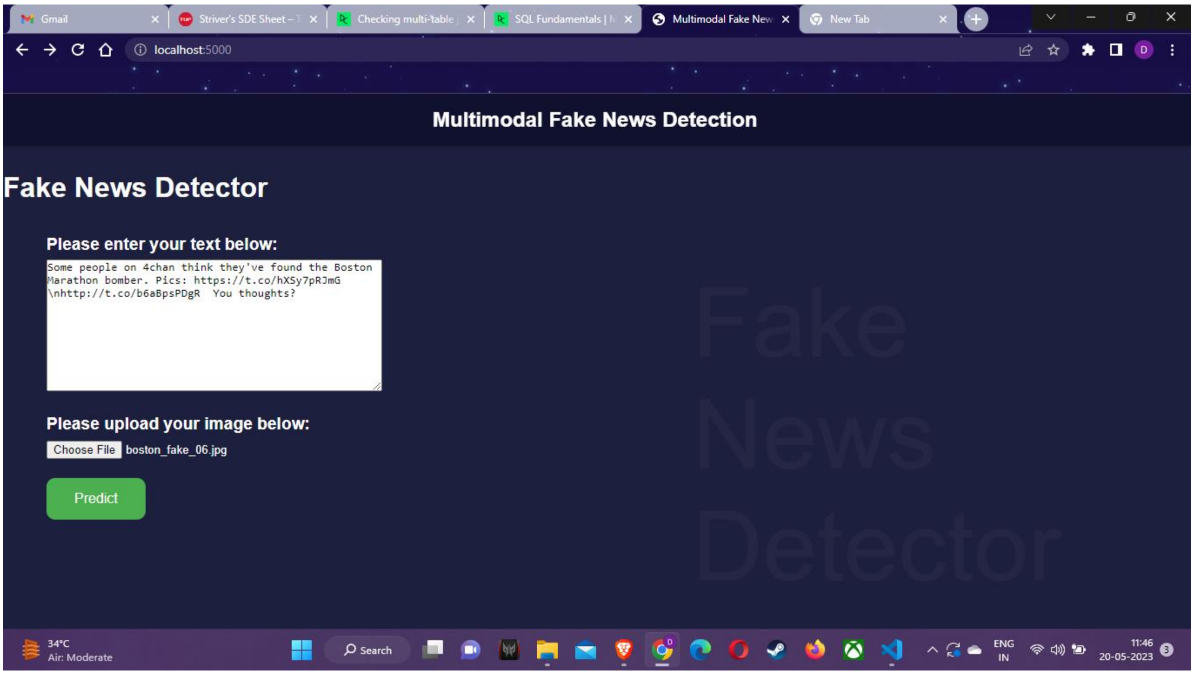

multimodal.ipynb
block4_conv2 (Conv2D) (None, 28, 28, 512) 2359808 ['block4_conv1[0][0]']
block4_conv3 (Conv2D) (None, 28, 28, 512) 2359808 ['block4_conv2[0][0]']
block4_conv4 (Conv2D) (None, 28, 28, 512) 2359808 ['block4_conv3[0][0]']
block4_pool (MaxPooling2D) (None, 14, 14, 512) 0 ['block4_conv4[0][0]']
block5_conv1 (Conv2D) (None, 14, 14, 512) 2359808 ['block4_pool[0][0]']
block5_conv2 (Conv2D) (None, 14, 14, 512) 2359808 ['block5_conv1[0][0]']
block5_conv3 (Conv2D) (None, 14, 14, 512) 2359808 ['block5_conv2[0][0]']
block5_conv4 (Conv2D) (None, 14, 14, 512) 2359808 ['block5_conv3[0][0]']
block5_pool (MaxPooling2D) (None, 7, 7, 512) 0 ['block5_conv4[0][0]']
reshape (Reshape) (None, 49, 512) 0 ['block5_pool[0][0]']
dense_4 (Dense) (None, 49, 32) 16416 ['reshape[0][0]']
batch_normalization_10 (BatchNormalization) (None, 49, 32) 128 ['dense_4[0][0]']
activation_10 (Activation) (None, 49, 32) 0 ['batch_normalization_10[0][0]']
dense_21 (Dense) (None, 49, 32) 1024 ['activation_10[0][0]']
dense_22 (Dense) (None, 49, 32) 1024 ['activation_10[0][0]']
dot_4 (Dot) (None, 49, 49) 0 ['dense_21[0][0]', 'dense_22[0][0]']
lambda_3 (Lambda) (None, 49, 49) 0 ['dot_4[0][0]']
14s completed at 10:20 PM

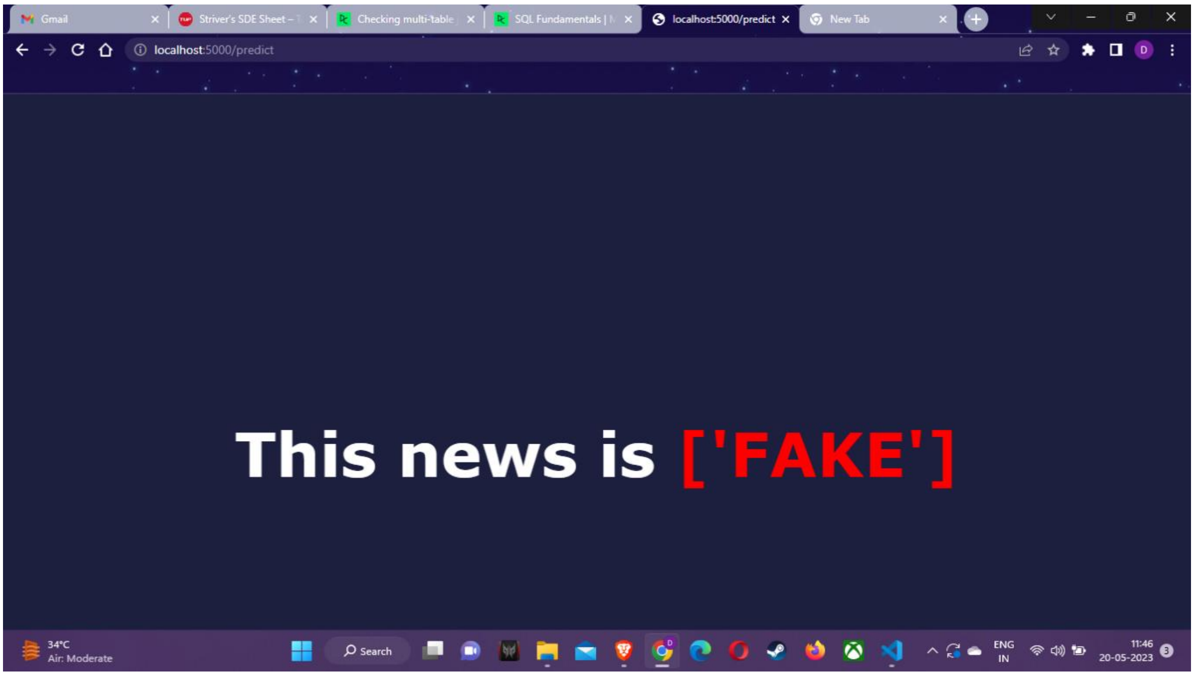

multimodal.ipynb
activation_23 (Activation) (None, 49, 49) 0 ['lambda_3[0][0]']
dense_23 (Dense) (None, 49, 32) 1024 ['activation_10[0][0]']
dot_5 (Dot) (None, 49, 32) 0 ['activation_23[0][0]', 'dense_23[0][0]']
dense_24 (Dense) (None, 49, 32) 1056 ['dot_5[0][0]']
dense_25 (Dense) (None, 49, 32) 1056 ['dot_5[0][0]']
dense_26 (Dense) (None, 49, 32) 1056 ['dot_5[0][0]']
dense_27 (Dense) (None, 49, 32) 1056 ['dot_5[0][0]']
batch_normalization_21 (BatchNormalization) (None, 49, 32) 128 ['dense_24[0][0]']
batch_normalization_22 (BatchNormalization) (None, 49, 32) 128 ['dense_25[0][0]']
batch_normalization_23 (BatchNormalization) (None, 49, 32) 128 ['dense_26[0][0]']
batch_normalization_24 (BatchNormalization) (None, 49, 32) 128 ['dense_27[0][0]']
activation_24 (Activation) (None, 49, 32) 0 ['batch_normalization_21[0][0]']
activation_25 (Activation) (None, 49, 32) 0 ['batch_normalization_22[0][0]']
activation_26 (Activation) (None, 49, 32) 0 ['batch_normalization_23[0][0]']
activation_27 (Activation) (None, 49, 32) 0 ['batch_normalization_24[0][0]']
average_2 (Average) (None, 49, 32) 0 ['activation_24[0][0]', 'activation_25[0][0]',


multimodal.ipynb
File Edit View Insert Runtime Tools Help Last saved at 10:21 PM
average_2 (Average) (None, 49, 32) 0 ['activation_24[0][0]', 'activation_25[0][0]', 'activation_26[0][0]', 'activation_27[0][0]']
dense_28 (Dense) (None, 49, 32) 1056 ['average_2[0][0]']
flatten (Flatten) (None, 25088) 0 ['block5_pool[0][0]']
batch_normalization_25 (BatchNormalization) (None, 49, 32) 128 ['dense_28[0][0]']
fc1 (Dense) (None, 4096) 102764544 ['flatten[0][0]']
activation_28 (Activation) (None, 49, 32) 0 ['batch_normalization_25[0][0]']
fc2 (Dense) (None, 4096) 16781312 ['fc1[0][0]']
dropout_41 (Dropout) (None, 49, 32) 0 ['activation_28[0][0]']
dense_2 (Dense) (None, 2048) 8390656 ['fc2[0][0]']
add_2 (Add) (None, 49, 32) 0 ['activation_10[0][0]', 'dropout_41[0][0]']
batch_normalization_8 (BatchNormalization) (None, 2048) 8192 ['dense_2[0][0]']
layer_normalization_2 (LayerNormalization) (None, 49, 32) 64 ['add_2[0][0]']
activation_8 (Activation) (None, 2048) 0 ['batch_normalization_8[0][0]']
flatten_1 (Flatten) (None, 1568) 0 ['layer_normalization_2[0][0]']
dropout_38 (Dropout) (None, 2048) 0 ['activation_8[0][0]']
28°C Haze
23:19 19-05-2023

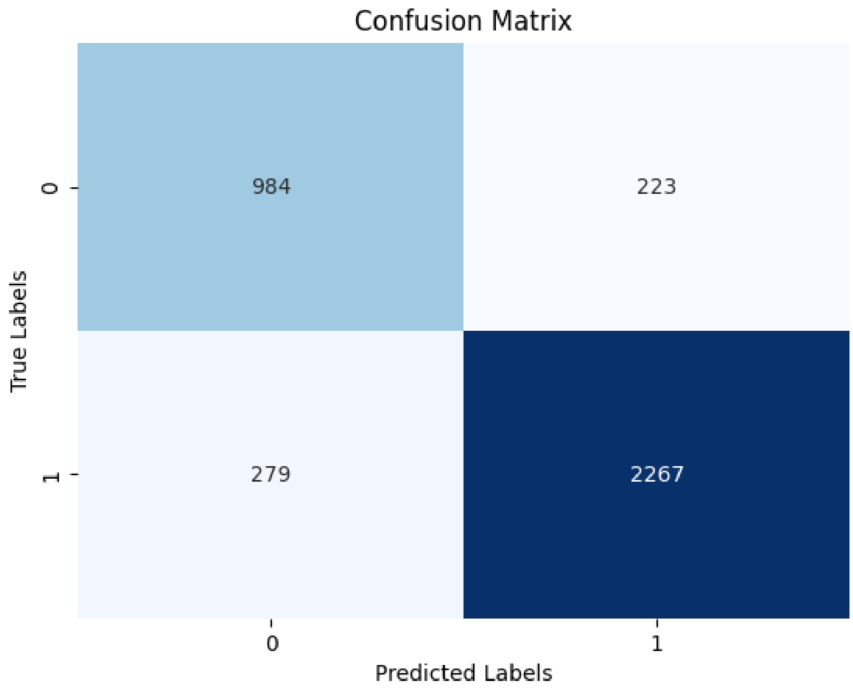

multimodal.ipynb
File Edit View Insert Runtime Tools Help Last saved at 10:21 PM
dense_29 (Dense) (None, 32) 50208 ['flatten_1[0][0]']
dense_3 (Dense) (None, 32) 65568 ['dropout_38[0][0]']
batch_normalization_26 (BatchNormalization) (None, 32) 128 ['dense_29[0][0]']
batch_normalization_9 (BatchNormalization) (None, 32) 128 ['dense_3[0][0]']
activation_29 (Activation) (None, 32) 0 ['batch_normalization_26[0][0]']
activation_9 (Activation) (None, 32) 0 ['batch_normalization_9[0][0]']
concatenate_2 (Concatenate) (None, 64) 0 ['activation_29[0][0]', 'activation_9[0][0]']
dropout_42 (Dropout) (None, 64) 0 ['concatenate_2[0][0]']
dense_30 (Dense) (None, 32) 2080 ['dropout_42[0][0]']
batch_normalization_27 (BatchNormalization) (None, 32) 128 ['dense_30[0][0]']
activation_30 (Activation) (None, 32) 0 ['batch_normalization_27[0][0]']
dropout_43 (Dropout) (None, 32) 0 ['activation_30[0][0]']
input_ids (InputLayer) [(None, 32)] 0 []
attention_mask (InputLayer) [(None, 32)] 0 []
dense_31 (Dense) (None, 1) 33 ['dropout_43[0][0]']
Total params: 148,112,961
28°C Haze
23:30 19-05-2023

Model Deployment using Flask:





Results:



Evaluation Metrics	Score
Training Accuracy	0.963
Accuracy Score	0.866240341060485
Precision Score	0.8152444076222038
Recall Score	0.7790973871733967

References

[1] Bhuvanesh Singh and Dilip Kumar Sharma, "Predicting image credibility in fake news over social media using multi-modal approach" *Neural Comput & Applic 34, 21503–21517 (2022)*, https://doi.org/10.1007/s00521-021-06086-4

[2] Qian, L., Xu, R. & Zhou, Z. MRDCA: a multimodal approach for fine-grained fake news detection through integration of RoBERTa and DenseNet based upon fusion mechanism of co-attention. Ann Oper Res (2022). https://doi.org/10.1007/s10479-022-05154-9

[3] Jing Jing, Hongchen Wu, Jie Sun, Xiaochang Fang, Huaxiang Zhang, Multimodal fake news detection via progressive fusion networks, Information Processing & Management, https://doi.org/10.1016/j.ipm.2022.103120.

[4] S. Singhal, R. R. Shah, T. Chakraborty, P. Kumaraguru and S. Satoh, "SpotFake: A Multi-modal Framework for Fake News Detection," 2019 IEEE Fifth International Conference on Multimedia Big Data (BigMM), Singapore, 2019, pp. 39-47, doi: 10.1109/BigMM.2019.00-44.

[5] Mohammad Hadi Goldani, Saeedeh Momtazi, Reza Safabakhsh, Detecting fake news with capsule neural networks, Applied Soft Computing, Volume 101, 2021, https://doi.org/10.1016/j.asoc.2020.106991.

[6] Q. Liao et al., "An Integrated Multi-Task Model for Fake News Detection," in IEEE Transactions on Knowledge and Data Engineering, vol. 34, no. 11, pp. 5154-5165, 1 Nov. 2022, doi: 10.1109/TKDE.2021.3054993.

[7] N. M. Duc Tuan and P. Quang Nhat Minh, "Multimodal Fusion with BERT and Attention Mechanism for Fake News Detection," 2021 RIVF International Conference on Computing and Communication Technologies (RIVF), Hanoi, Vietnam, 2021, pp. 1-6, doi: 10.1109/RIVF51545.2021.9642125.

[8] Uppada, S.K., Patel, P. & B., S. An image and text-based multimodal model for detecting fake news in OSN's. J Intell Inf Syst (2022). https://doi.org/10.1007/s10844-022-00764-y

[9] Saqib Hakak, Mamoun Alazab, Suleman Khan, Thippa Reddy Gadekallu, Praveen Kumar Reddy Maddikunta, Wazir Zada Khan, An ensemble machine learning approach through effective feature extraction to classify fake news, Future

Generation Computer Systems, Volume 117,2021, Pages 47-58, https://doi.org/10.1016/j.future.2020.11.022.