FakeTweet Busters: A combination of BERT and Deepfake detection to resolve the spreading of fake news.

Department of Computer Science and Engineering
Netaji Subhas University of Technology
New Delhi

Name of the Student	**Roll Number**
Shubhangee Pal	2020UCO1574
Bhagyashree Das	2020UCO1615
Amrisha Das	2020UCO1687

Under supervision by:
Dr. Preeti Kaur

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Introduction

The ubiquity of social media platforms such as Twitter has reshaped the landscape of information dissemination, offering unparalleled accessibility but also exposing users to the proliferation of misinformation and "fake news". This phenomenon, disguised as legitimate news, poses significant risks by eroding trust in media, swaying public opinion, and potentially influencing political decisions.

This project endeavors to confront the challenge of identifying fake tweets by harnessing the combined capabilities of two cutting-edge technologies: BERT (Bidirectional Encoder Representations from Transformers) and deep fake detection. BERT, renowned for its adeptness in discerning textual nuances, holds promise in identifying key features indicative of fake news within tweet content. Concurrently, deepfake detection techniques offer a complementary layer of analysis by scrutinizing accompanying images and videos for signs of manipulation or tampering.

The detection of deepfakes necessitates sophisticated algorithms that meticulously examine visual and auditory elements for inconsistencies or artifacts indicative of manipulation. Integrating BERT-based textual analysis with advanced deepfake detection methodologies, the project aims to establish a comprehensive framework for identifying fake tweets. By synergizing the strengths of both approaches, the system can cross-reference textual content with visual and auditory cues, thus enhancing its capacity to detect sophisticated forms of misinformation that might otherwise elude conventional textual analysis methods.

This holistic approach represents a significant advancement in combating the dissemination of misinformation online, empowering users and platforms alike with enhanced capabilities to discern and mitigate the impact of fake tweets.

Motivation

The motivation for this project stems from two primary reasons:

I. The Global Crisis of Fake News: The proliferation of fake news has become a global phenomenon, posing a significant threat to the integrity of online information and societal well-being. A 2023 report by the Reuters Institute for the Study of Journalism found that over 70% of internet users worldwide have encountered fake news. This widespread exposure to misinformation can have detrimental consequences like distorting public perception on critical issues like healthcare, politics, and the environment, influencing electoral outcomes by swaying public opinion through biased or fabricated information, inciting societal discord and even violence by fueling polarization and distrust. Given these significant risks, addressing the challenge of fake news necessitates the development of innovative and effective solutions

II. The Need for Advanced Detection Techniques: As the creators of fake news continually adapt their tactics, staying ahead requires sophisticated detection methods. A particularly concerning development is the rise of deepfakes, which are synthetic media created using artificial intelligence to manipulate videos or images, making them appear real. A 2019 study by the University of California, Berkeley, found that over 60% of participants were unable to distinguish between real and deepfake videos. This highlights the growing challenge posed by deepfakes and underscores the urgency for robust detection methods capable of identifying not only textual manipulation but also visual deception.

Furthermore, the ever-evolving nature of fake news tactics demands persistent innovation in countermeasures. The emergence of deepfakes exemplifies the dynamic landscape of misinformation, necessitating adaptive and multifaceted approaches to effectively combat its spread.

In response to these challenges, this project seeks to explore the synergistic potential of two promising technologies:

- BERT (Bidirectional Encoder Representations from Transformers): This powerful language model will be utilized to analyze the textual content of tweets, identifying characteristics commonly associated with fake news, such as unusual vocabulary, sensationalized language, and grammatical errors.

- Advanced Deepfake Detection Techniques: By incorporating state-of-the-art image and video analysis methods, the project aims to detect potential deepfakes embedded within tweets, offering a more comprehensive analysis of potential deception.

By combining these two approaches, the project seeks to develop a robust and comprehensive framework for identifying fake tweets. This interdisciplinary effort holds significant promise for:

Enhancing the accuracy and effectiveness of fake tweet detection.

Preserving trust in online information and fostering a more informed and truthful online environment.

Contributing to the integrity of social and political discourse by mitigating the influence of misinformation.

Through this innovative approach, the project aims to take a significant step towards addressing the global challenge of fake news and promoting a more reliable and trustworthy online ecosystem.

Literature Survey

S.no	Paper	Authors	Description	Results	Shortcomings
1	Multimodal Fusion with BERT and Attention Mechanism for Fake News Detection	Nguyen Manh Duc Tuan, Pham Quang Nhat Minh	The research paper presents a novel method for detecting fake news by fusing multimodal features derived from textual and visual data. The method utilizes a pre-trained BERT model for learning text features and a VGG-19 model pre-trained on the ImageNet dataset for extracting image features. Additionally, the paper introduces a scale-dot product attention mechanism to capture the relationship between text and visual features.	The experimental results highlight the significance of using a BERT model pre-trained on Twitter data, as it outperforms BERT models trained on general domain corpora. The research paper delivers a robust multimodal approach for identifying fake news, leveraging both textual and visual features with an innovative attention mechanism.	The introduction lacks a clear research gap, explicit definition of fake news, and motivation for the chosen multimodal approach. The dataset choice is inadequately explained, and the problem statement is ambiguous. The related work section lacks recent citations, thorough critique of existing models, detailed comparison metrics, and consideration of ethical implications.
2	L3Cube-MahaHate: A Tweet-based Marathi Hate Speech Detection Dataset and BERT models	Abhishek Velankar, Hrushikesh Patil, Amol Gore,Shubham Salunke,Raviraj Joshi	The research paper discusses the creation of L3Cube-MahaHate, the first significant Hate Speech Dataset in Marathi. The dataset consists of over 25,000 tweets labeled into four classes: hate,	The findings indicate that the non-trainable fast text mode for CNN and LSTM outperforms its trainable counterpart, and the MahaBERT model provides the best classification results.	There is a scarcity of research on hate speech detection in the Marathi language, indicating a gap in addressing online content concerns in this specific

			offensive, profane, and not. The paper outlines the data collection and annotation process, as well as the challenges faced. Baseline classification results using deep learning models including CNN, LSTM, and Transformers are presented.		linguistic context. Furthermore, general text classification in Marathi has been relatively overlooked, revealing a broader need for research and technological development to cater to the linguistic nuances of Marathi content online.
3	“Liar, Liar Pants on Fire”: A New Benchmark Dataset for Fake News Detection	William Yang Wang	The paper introduces a new benchmark dataset called LIAR for fake news detection and fact-checking, containing 12.8K manually labeled short statements collected from POLITIFACT.COM over a decade.The paper proposes a hybrid convolutional neural network that integrates metadata with text and demonstrates improved performance for automatic fake news detection compared to text-only deep learning models.	The results show that the CNN model outperformed other models, especially when considering all metadata and text, indicating significant improvements for fine-grained fake news detection.	The paper introduces the LIAR dataset for fake news detection, providing a valuable resource but lacking thorough evaluation metrics and discussions on dataset challenges, potential biases, and temporal dynamics. Further exploration of the impact of individual meta-data features and external validation would enhance the research's

					credibility and applicability.
4.	Exploiting CT-BERT and Ensembling Learning for COVID -19 Fake News Detection	Anna Glazkova, Maksim Glazkov, Timofey Trifonov	The paper addresses the issue of fake news related to the COVID-19 pandemic, which can cause panic and misinformation among readers. It proposes an approach that utilizes a transformer-based ensemble of COVID-Twitter-BERT (CT-BERT) models for fake news detection. The paper describes the models used, text preprocessing techniques, and the addition of extra data to improve the approach's quality.	The results give an approach for COVID-19 fake news detection using CT-BERT ensemble. The Best model achieved 98.69 weighted F1-score on test set.	The paper proposed effective COVID-19 fake news detection using CT-BERT. It suggested future work on training techniques and hybrid models and experimentation with different training and data augmentation techniques. But some of the drawbacks included lack of detailed comparative analysis of text preprocessing technique and it was observed converting hashtags into words did not show clear benefits.
5.	FaceForensics++: Learning to Detect Manipulated Facial Images	Andreas Rossler, Davide Cozzolino, Luisa Verdoliva,	The paper covers face manipulation methods, multimedia forensics, and related papers. It mentions various face manipulation	The results show that the paper proposed automated benchmark for forgery detection with random compression/dimensions. It also Evaluated	The paper states current facial manipulation methods can be detected by forgery

		Christian Riess, Justus Thies, Matthias Nießner	techniques and detection methods. Some methods used include Face2Face, FaceSwap, DeepFakes, NeuralTextures for facial manipulation detection. Also discusses datasets for forensic analysis, including image and video manipulations. It detects manipulated facial images using deep learning techniques.	state-of-the-art detection methods and forgery detection pipeline.	detectors. It introduced a novel dataset for manipulated faces exceeding existing datasets and proposed a standardized benchmark for detecting state-of-the-art manipulations. Both dataset and benchmark are publicly available for research and transfer learning. But evaluation was restricted to facial manipulation methods with specific conditions and there is a lack of benchmark for forgery detection in digital media forensics.
6.	DeepFakes and Beyond: A Survey of Face Manipulation and Fake Detection	Ruben Tolosana, Ruben Vera-Rodriguez, Julian Fierrez, Aythami Morales and Javier Ortega-Garci	The paper provides a comprehensive survey of the implications of the widespread availability of large-scale public databases and the rapid advancements in	The authors discussed numerous studies and approaches for detecting facial manipulation. They provided detailed insights into the specific approaches, evaluation methods, and results obtained by various detection	The paper explores the societal impact of deep learning, particularly Generative Adversarial Networks (GANs), on creating realistic fake

			deep learning techniques, particularly Generative Adversarial Networks (GANs), in creating highly realistic fake content and its potential impact on society in the era of fake news. The authors reviewed techniques for manipulating face images, including four main types of facial manipulation: entire face synthesis, identity swap (DeepFakes), attribute manipulation, and expression swap.	systems. Many studies have achieved high accuracy in detecting manipulated content, often close to 100%, using deep learning based techniques.	content like images and videos. The authors emphasize the need for improved generalization ability and fusion techniques for the detection of fake content, and discuss the evolution of GAN-generated fake images and videos based on recent techniques. The paper highlights the challenging and dangerous approaches of face morphing, face de-identification, and face synthesis based on audio or text and provides an in-depth analysis of the deepfake detection challenge.

Problem Statement

The global proliferation of fake news, specifically through fabricated tweets, poses a critical threat to the integrity and trust of online information around the world. Traditional methods for identifying such content, largely reliant on textual analysis, are increasingly ineffective due to several factors:

1. Evolving Tactics: Creators of fake content are constantly adapting their methods, employing techniques like deepfakes (manipulated videos or images) to create seemingly genuine content that bypasses traditional analysis.

2. Limited Scope: Textual analysis alone often fails to capture the full context of a tweet, overlooking crucial visual information that might expose its deceptive nature.

This inadequacy of existing methods necessitates the development of a more robust and comprehensive solution capable of addressing the evolving landscape of deceptive online content across the globe. To achieve this, this research project proposes a novel approach that combines the strengths of textual analysis and deep fake detection.

By harnessing the capabilities of BERT, an advanced language model renowned for its contextual understanding of text, to uncover discernible markers indicative of fake news within tweet content, alongside the implementation of cutting-edge image and video analysis techniques to identify potential instances of deepfake manipulation, the research aims to construct a comprehensive framework for detecting and flagging deceptive tweets.

This multifaceted approach endeavors to overcome the inherent limitations of existing methodologies and provide a more resilient solution to combat the propagation of misinformation online. Through the integration of BERT's analytical prowess with deepfake detection techniques, the research seeks to empower users and online platforms with the necessary tools to effectively discern and mitigate the impact of fake tweets, thus safeguarding the credibility and trustworthiness of online information ecosystems.

Objective

This project aims to address the critical and ever-growing issue of fake news, specifically focusing on fabricated tweets. A study by the University of Oxford in 2017 estimated that 19% of tweets containing political hashtags during the 2017 French election originated from automated bots. To combat this challenge, this project seeks to develop a reliable and efficient method for identifying fake tweets, leveraging the combined strengths of two distinct approaches:

1. Textual Analysis: Utilizing a powerful language model like BERT, the project will analyze the textual content of tweets, searching for specific linguistic patterns and characteristics frequently associated with fake news. These characteristics may include:

- Unusual word choices or sentence structures
- Excessive use of exclamation points and emojis
- Grammatical errors and typos
- Highly sensationalized language designed to evoke strong emotions

2. Deepfake Detection: Recognizing the increasing sophistication of fabricated content, the project will incorporate advanced image and video analysis techniques to identify potential deepfakes embedded within the tweet. Deepfakes are synthetic media where a person's face or voice is replaced with another's, often used to spread misinformation.

By combining these two approaches, the project aims to create a more comprehensive and robust framework for flagging deceptive tweets. This multifaceted approach has the potential to significantly improve the accuracy and effectiveness of combating the spread of misinformation online, fostering a more informed and truthful online environment.

Methodology:

Currently both the functionalities - fake tweet detection and Deepfake detection for non-textual content has been done separately. The methodologies for both have been explained separately below.

Fake tweet detection:

We have selected the dataset which has the following columns - screen_name, text, account and class_type.
The main aim was to compare different language models, techniques, LLM's such that we are able to conclude which will serve the best to meet our needs.
Applying NLP Techniques for Fake Tweet Detection:
Here's an overview of how you can utilize various techniques for fake tweet detection:

1. **Bag-of-Words (BoW)**: is a simplified representation of a document or collection of text data. It focuses solely on the presence and frequency of individual words, ignoring their order and context
2. **Character-Level CNN (CharCNN)**:It is a type of deep learning model used for text classification and analysis. Unlike traditional CNNs that operate on words or larger units, CharCNNs work at the character level. This allows them to handle out-of-vocabulary words (words not present in the training data) and to capture subtle information encoded in character sequences.
3. **BERT**: It is a powerful pre-trained language model developed by Google AI. It uses a novel technique called transformers to learn contextual representations of words, capturing their meaning based on the surrounding words in a sentence.
4. **DistilBERT**:It is essentially a smaller and faster version of BERT (Bidirectional Encoder Representations from Transformers), designed by Google AI to address two main limitations of the original model: computational cost and resource requirements.
5. **RoBERTa**: It is similar to BERT, but with a different pre-training objective and architecture, potentially offering improved performance on specific tasks.
6. **XLNet**:It is similar to BERT, but with a permutation language modeling approach that considers all possible word orders, potentially capturing deeper context and relationships within the text.

For DeepFake detection of non textual content:
Deepfake: It is an artificially generated image or video that manipulates a person's appearance to make them look like they are doing or saying something they never did. Detecting deepfakes in images involves utilizing various techniques to identify inconsistencies or manipulation artifacts introduced during the creation process.
Gradio: It is an open-source Python library designed to simplify the process of building web interfaces for your machine learning models, APIs, or even any arbitrary Python function. It allows you to create user-friendly and interactive interfaces without requiring expertise in web development like JavaScript, CSS, or HTML.
facenet_pytorch: for face detection and recognition

PIL.Image: for image processing
pytorch_grad_cam: for visualizing the parts of an image that contribute to a specific prediction
1. **Deep Learning**: Deep Learning (DL) is a subfield of Artificial Intelligence (AI) concerned with training artificial neural networks to learn from data and perform tasks similar to how the human brain works.
1.a. **Convolutional Neural Networks (CNNs):** The workhorse of deepfake detection, trained to recognize patterns and inconsistencies in images signifying manipulation. Pre-trained models like VGG16 and ResNet provide a strong foundation, further fine-tuned on deepfake datasets.

- **Generative Adversarial Networks (GANs):** Though not solely for detection, GANs can be used for "adversarial training" by having a "generator" create realistic deepfakes and a "discriminator" learn to differentiate real from fake, potentially improving detection capabilities.

2. Computer Vision Techniques:

- **Image segmentation:** Identifying and analyzing different regions within an image, like facial areas, can help detect inconsistencies in skin texture, lighting, and other features often targeted for manipulation.
- **Facial landmark detection:** Identifying and analyzing key facial features like eyes, nose, and mouth can reveal inconsistencies in their proportions, movement patterns, or blinking, potentially indicating manipulation.

<u>Implementation and Work done till date:</u>

Based on our plan of action, we have been moving steadily towards the completion of our desired objectives. We decided to initially split our project into 2 halves out of which we have been able to successfully complete the first part.
The first being independent models:

I. Detection of false tweets on twitter's textual content.

We have used the following NLP techniques **- Bag of Words (BoW), CharCNN, BERT, DistillBERT, RoBERTa, XLNet along with Logistic Regression, SVM, Random Forest** in order to calculate the performance parameter get the desired best result for it.

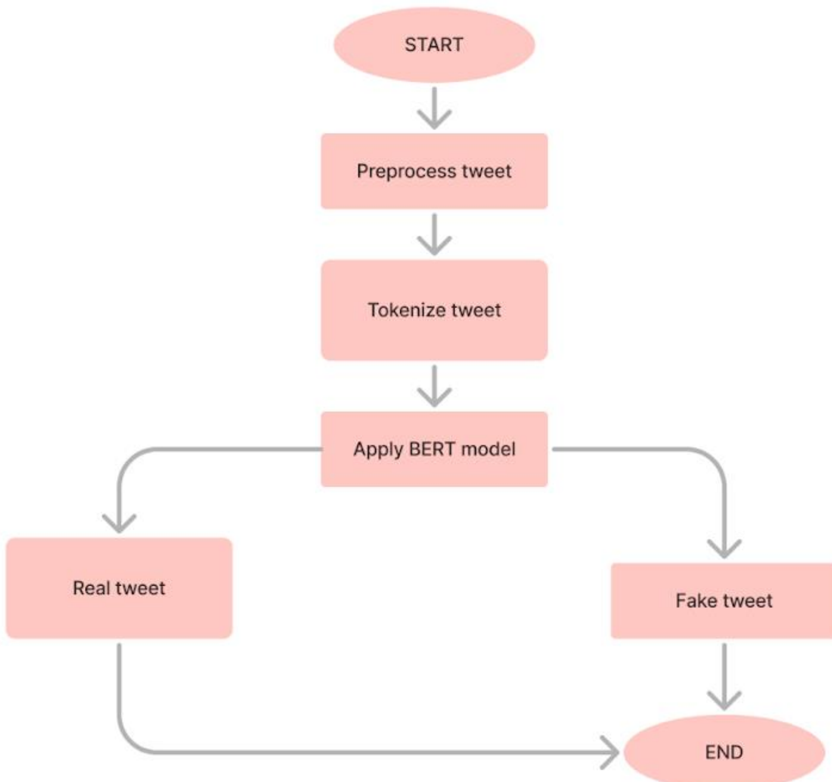

Fig 1

II. Deepfake detection for the non textual data.

We first upload the photo that we wish to check upon, based on MTCNN and InceptionResnetV1. It combines face detection, pre-trained model prediction, Grad-CAM visualization, and confidence score calculation into a single function. The Gradio interface makes this functionality accessible through a user-friendly web interface, allowing users to upload images and see the predicted class (real or fake) along with a visualization of the model's focus areas for the prediction.

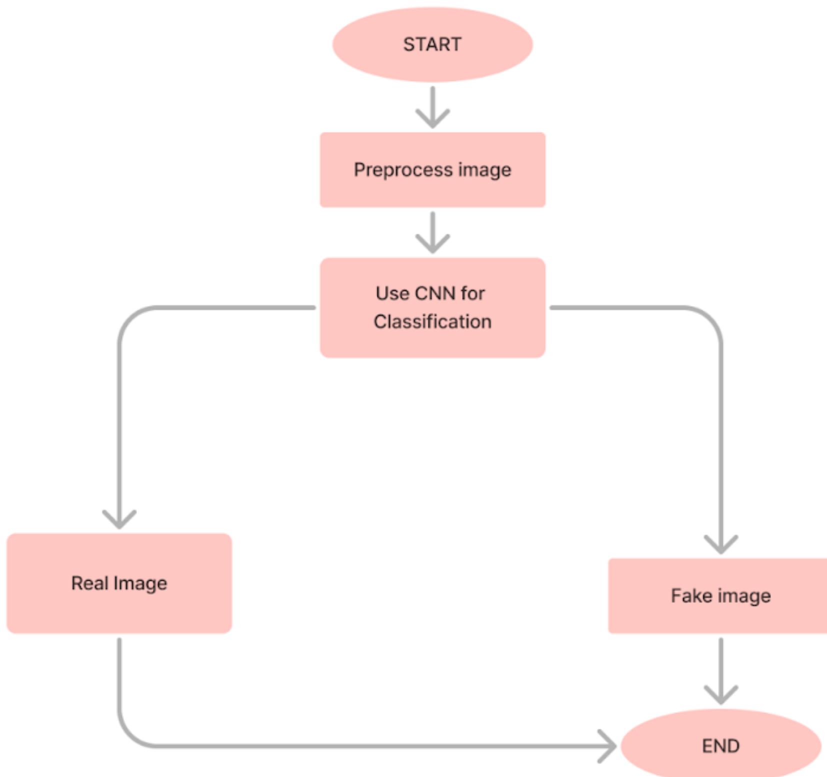

Fig 2

Results:

	prediction	gold
0	human	human
1	human	human
2	bot	human
3	bot	bot
4	human	human

Fig 3: Model prediction vs Actual prediction

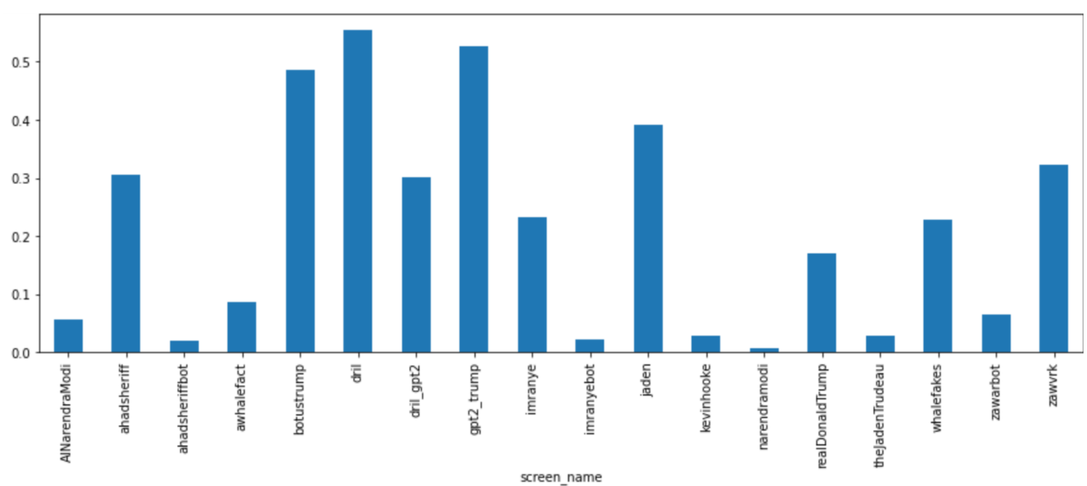

Fig 4. Accounts that give fake news

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Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

              precision    recall  f1-score   support

           0      0.841     0.749     0.792      1278
           1      0.774     0.859     0.814      1280

    accuracy                          0.804      2558
   macro avg      0.807     0.804     0.803      2558
weighted avg      0.807     0.804     0.803      2558
```

Fig 5. Performance Metric

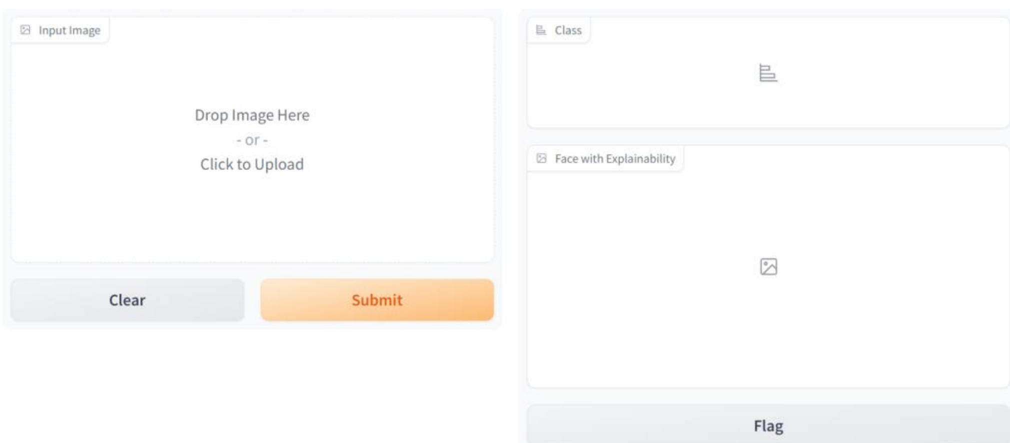

Fig 6. The interface for DeepFake detection of images

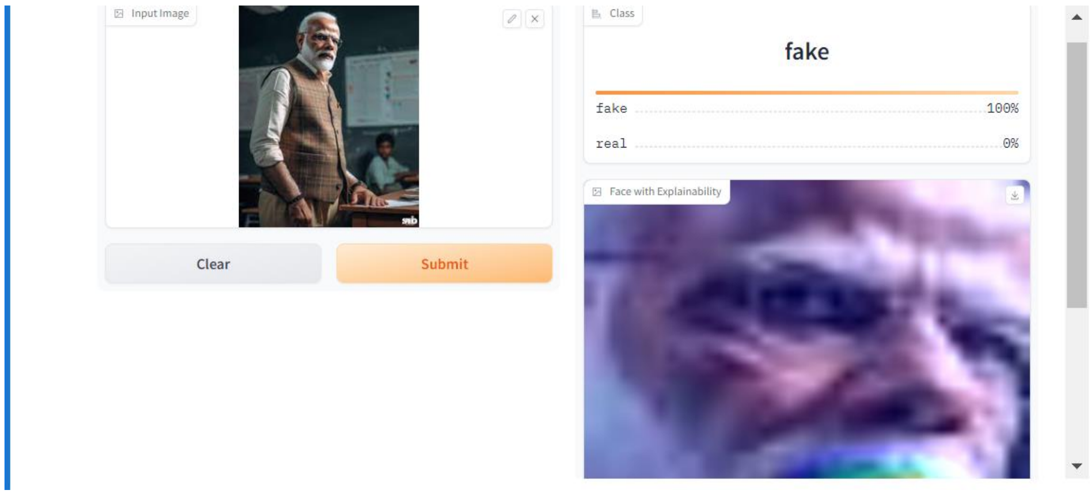

Fig 7. Fake image detected based on the AI generated image.

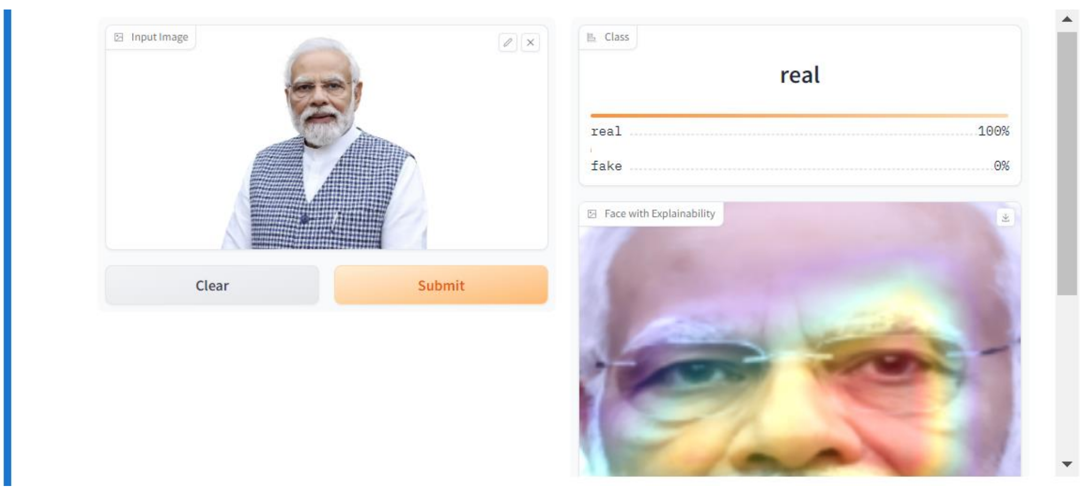

Fig 8. Real image detected based on the photo on the official website.

Future work:

As we work towards continuous improvement, here are some exciting future functionalities we are exploring:

- **Integrated Analysis for Comprehensive Fake Tweet Detection:** While this project establishes a robust framework for identifying fake tweets through individual modalities, future work aims to leverage the project's potential for even more comprehensive analysis by combining the strengths of both techniques:

  Deepfake detection: This component, currently being explored, aims to identify potential image manipulation within the tweet, uncovering any visual deception through advanced techniques.

  BERT-based bot detection: By capitalizing on the project's existing capability, we will further refine the process of differentiating between human-generated and bot-generated tweets.

  This multimodal approach holds the potential to significantly enhance the accuracy and reliability of fake tweet detection. By analyzing both the textual content and the visual elements of a tweet, the project can offer a more holistic and comprehensive assessment of its authenticity. This integrated approach can be particularly valuable in combating deepfakes that combine manipulated images with fabricated text, creating a seemingly genuine tweet.

- **Expansion to Audio and Video Detection:** Our project will extend deepfake detection to encompass audio and video content, bolstering its efficacy against multimedia-based misinformation. This involves incorporating techniques for audio analysis - detecting synthetic voices and audio splicing and video analysis- identifying deepfakes and visual inconsistencies.

- **Expanding Language Coverage:** While this project demonstrates effectiveness in identifying fake tweets within the English language, future efforts will focus on broadening its reach to encompass a multilingual scope. This expansion is crucial to address the global challenge of fake news effectively. To do this we can use Multilingual BERT Models. We aim to utilize state-of-the-art multilingual BERT models trained on massive datasets of text in diverse languages.
  By pursuing these directions, the project aspires to evolve into a robust and inclusive framework capable of combating fake news on a global scale.

- **Exploring an Alerting Extension:** To further empower users, future work envisions integrating an alerting extension. When enabled, this feature will proactively notify users when they encounter a tweet containing potentially fake content, including images and videos. This notification system will leverage the project's combined deepfake detection and BERT-based analysis to offer real-time guidance, promoting increased user awareness and fostering a more critical approach towards online information.

While this project establishes a robust foundation for identifying fake tweets, the team remains committed to continuous development and user empowerment. Future work envisions the integration of several innovative features, such as multilingual capabilities, proactive user alerts, and enhanced detection across various media formats (audio and video). These advancements hold immense potential to significantly enhance the project's impact, solidifying its role as a vital tool in the fight against online misinformation.

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