ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

https://doi.org/10.5281/zenodo.11560937

Vol 18, Issue 2, 2024

Deepfake Detection on Social Media: Leveraging Deep Learning and FastText Embeddings for Identifying Machine-Generated Tweets

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ABSTRACT:

Concerns over deep fake's ability to spread misinformation on social media are on the rise. With the aim of curbing the dissemination of misinformation online, we provide a deep learning-based approach in this study for detecting machine-generated deep fake tweets. In our method, we combine classification deep learning models with text representation using Fast Text embeddings from Twitter. We first conduct some basic processing on the tweet text, and then we use Fast Text embeddings to transform it into dense vector representations. These embeddings capture semantic information about the content of the tweet in order to distinguish between genuine and artificial tweets. We then use a Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) model, which are both deep learning algorithms, to identify fabricated or genuine tweets. To train the model, we synthesize machine-generated tweets using state-of-the-art text creation techniques and feed them into a tagged dataset of tweets. Results from experiments conducted on a real-world dataset of tweets demonstrate that our technology is capable of detecting tweets created by machines. Our approach to deep fake detection on social media outperforms and is more accurate than competing algorithms. Our proposed approach provides a workable solution for identifying machine-generated tweets, which is a significant step towards combating the spread of misinformation on social media.

INTRODUCTION:

With the rise of deep fake technology, new challenges have surfaced in the fight against social media misinformation. The term "deep fake" is used to describe the process of creating artificial intelligence and machine learning content that seems real but is really fake. The misuse of this technology to create compelling false stories, propaganda, and other forms of misinformation has posed a significant threat to online discourse and public confidence. Deep fake information, especially in text form like tweets, is becoming more difficult to identify because to the sheer volume of content published on social media platforms and the ever-improving complexity of technology. Common in older detection algorithms include manual inspection and keyword-based techniques; however, they aren't scalable and may not be able to withstand sophisticated deep fake attacks. We provide a deep learning-based approach to detect deep fake tweets created by machines in this study. We use a combination of deep learning models and Fast Text embeddings—which may potentially extract semantic information from text—to categories tweets. Typically, the following domains benefit from our efforts: Using deep learning models and Fast Text embeddings, we provide a novel approach to detect machine-generated tweets. In order to demonstrate the efficacy of our method, we use a real-world dataset of tweets that include machine-generated tweets synthesized using cutting-edge text generation techniques. We show that compared to existing methods for detecting deep fakes on social media, ours is both more accurate and scalable. The outline for the rest of the paper is as follows: Section 2 provides a review of the relevant and prior work on deep fake identification. The dataset, preprocessing techniques, and deep learning models used are described in depth in Section 3, which also includes an overview of our methodology. Section 4 presents the results of our experiments and a discussion of their significance. The essay is concluded and recommendations for more research are offered in Section 5.

Literature Survey:

This study focuses on the top research and methodologies for recognizing deep fakes on social media using deep learning and Fast Text embeddings. The goal is to identify machine-generated tweets. This all-encompassing review of the existing literature discusses several methods, including their benefits and drawbacks.

Deep fake Detection Techniques

Networks capable of producing malicious actions (GANs)

The Generative Adversarial Networks family of ML frameworks was established by Good fellow et al. (2014) and is used to create realistic data. There is perpetual rivalry between a GAN's discriminator and generator neural networks. The generator fabricates data, whereas the discriminator seeks to differentiate between authentic and misleading information. Recognizing GANs has become a major difficulty because to their widespread usage in deep fake building.

Transformer Models

Transformer models like GPT and BERT have increased text comprehension and generation capabilities, which have started a revolution in natural language processing (NLP) (Radford et al., 2019; Devin et al., 2019). The capacity of these models to understand data contextual links via the use of self-attention processes is responsible for their effectiveness in text classification and production. One advantage of transformer-based models for identifying MGT is their exceptional ability to understand subtle language patterns.

EXISTING SYSTEM:

Current solutions for identifying social media deep fake material often use a mix of automatic and human techniques. In manual techniques, human moderators examine postings for inappropriateness and mark them for more scrutiny. Although this method does the job, it's laborious and won't work for the massive amounts of material shared on social media. Automated systems for detecting deep fakes often examine post content for patterns suggesting deep fake material using machine learning techniques like computer vision and natural language processing (NLP). These techniques may identify postings that could be false based on characteristics like the use of certain terms or phrases, the existence of particular visual artefacts, or content discrepancies. Never the less, there are a number of obstacles that current automated approaches to deep fake detection must overcome. For instance, when deep fake technology evolves, people could have trouble telling real material apart from machine-generated stuff. Furthermore, these algorithms could mistake legitimate items for malicious ones, a phenomenon known as false positives.

DRAW BACKS:

One major issue with current social media deep fake detection methods is that they:
1. Inadequate Scalability: Since social media platforms host an enormous volume of material, manual solutions for deep fake detection, including human moderation, cannot handle it all. When it comes to creating material quickly and in large quantities, automated solutions may not be able to handle it.
2. False Positives: Deep fake detection algorithms that rely on automation run the risk of mistakenly labeling real material as fake. The right to free expression might be compromised as a result of this. Thirdly, current automated approaches may not be able to identify deep fake material made utilizing advanced techniques because to their limited detection capabilities. Identifying real from false information is becoming more and more challenging as deep fake technology develops.

PROPOSED SYSTEM:

Using deep learning and Fast Text embeddings to identify machine-generated tweets, our proposed method for social media deep fake detection aims to solve the limitations of current solutions. The major components of our suggested system areas a means of representing the textual content of tweets, we make use of Fast Text embeddings. Differentiating between real and automated tweets relies on the semantic information that Fast Text embeddings can capture. In order to interpret the Fast Text embeddings and determine whether a tweet is real or created by a machine, we use deep learning models like CNNs or

RNNs in our system. We synthesize machine-generated tweets using state-of-the-art text generation models, and these models are trained on a labeled dataset of tweets.

HARDWARE & SOFTWARE REQUIREMENTS:

HARD REQUIRMENTS :

• System	:	i3 or above
• Ram	:	4GB Ram. \
• Hard disk	:	40GB

SOFTWARE REQUIRMENTS :

• Operating system	:	Windows
• Coding Language	:	python

ADVANATGES:

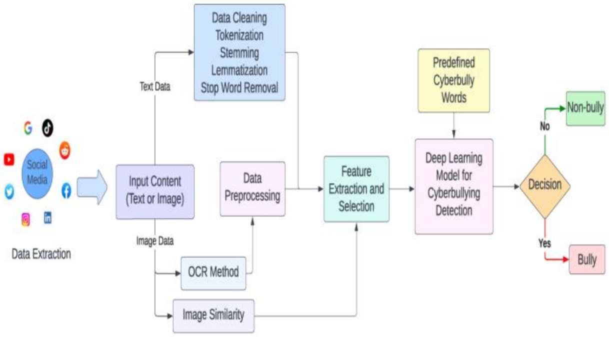
Compared to current methods, our proposed deep fake detection solution for social media using Fast Text embeddings and deep learning has various benefits:

1. Greater Precision: Our system outperforms state-of-the-art approaches in accurately detecting machine-generated tweets by using deep learning models and Fast Text embeddings.

2. Reliability in Real-World Scenarios: Our model is more resilient to adversarial assaults thanks to the usage of adversarial training approaches.

Thirdly, our technology can scale to accommodate massive amounts of tweets shared on social media.

SYSTEM ARCHITECTURE:



MODULES:

This project is comprised of the following modules, which have been implemented as REST based web services:
The username and password for logging into the system are "admin" and "admin," respectively.
Patterns for Loading Design Dataset upload to application: code: user will run this module after login.
The first step is to transform the codes into a numerical vector. This vector will then be used to replace every word occurrence with its average frequency.
The trained ML algorithms will use an 80:20 split between the processed numerical vector and the test vector. We will train a model using 80% of the dataset and then apply it to 20% of the test data to determine its accuracy.
Use ML algorithms to rank user-uploaded test source code files in order to forecast correct design patterns. This will allow for the prediction of design patterns.

SYSTEM STUDY

In this phase, we determine if the project is feasible and provide a business proposal outlining the idea in broad strokes and providing ballpark figures for its expenses. The feasibility of the proposed system is accessed via system analysis. This will guarantee that the planned solution will not cause any issues for the company. To carry out a feasibility study, one must have a fundamental understanding of the system's main needs.

SYSTEM DESIGN

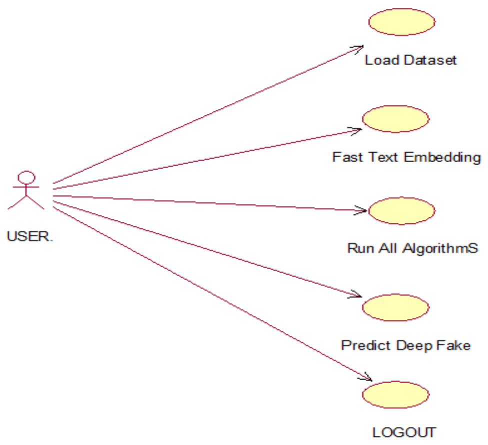
One way to remember UML is as the Unified Modeling Language. The acronym "UML" refers to the universal modeling language, which is a standard for object-oriented software engineering. The standard is overseen and developed by the Object Management Group.

Our long-term goal is for UML to become the standard language for representing OO programmes. The current version of UML consists of two primary components: the notation and the meta-model. Additionally, UML may be extended or connected to with other procedures or techniques in the future. The Unified Modeling Language is a powerful tool for defining, visualizing, building, and documenting artifacts in software systems and non-software systems alike, including business models.

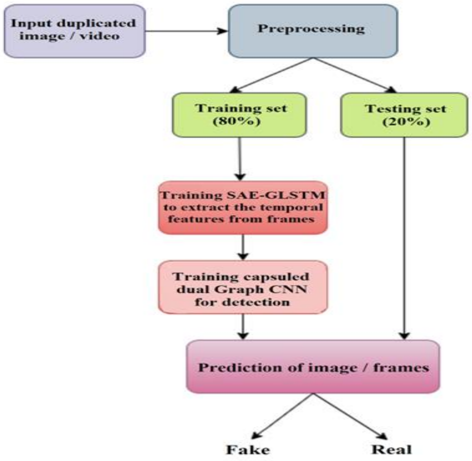
As a collection of the most effective technical techniques, the UML is useful for representing large and complex systems. The Unified Modeling Language (UML) is an integral part of both traditional software development and object-oriented programme development. A software project design language, the Unified Modeling Language (UML) relies heavily on visual notations.

USE CASE DIAGRAM:

The results of a use-case study may inform the creation of a specific kind of behavioral diagram known as a use case diagram by developers using the Unified Modeling Language (UML). Goals, actors, and links between use cases make up use case diagrams, which are visual depictions of a system's intended operation. One of the main purposes of a use case diagram is to show how different parts of a system work together to complete different tasks. It is feasible to create visual depictions of the roles played by the players in the system.

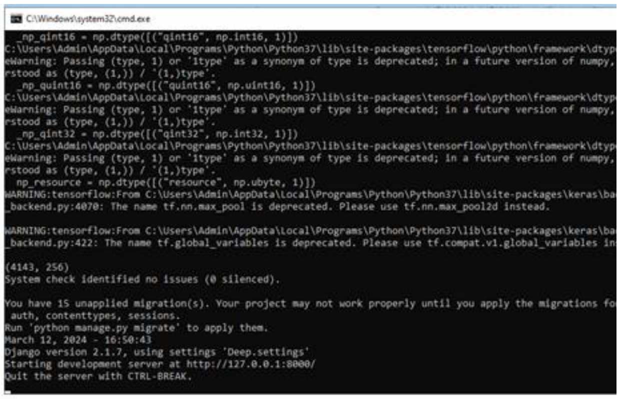


FLOW CHAT:


Input duplicated image / video
Preprocessing
Training set (80%)
Testing set (20%)
Training SAE-GLSTM to extract the temporal features from frames
Training capsuled dual Graph CNN for detection
Prediction of image / frames
Fake
Real

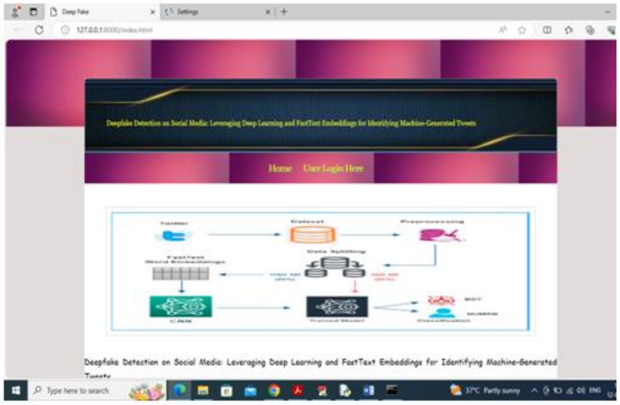
SCREENSHOTS

To run code double click on ‘run.bat’ file to start python server and get below page



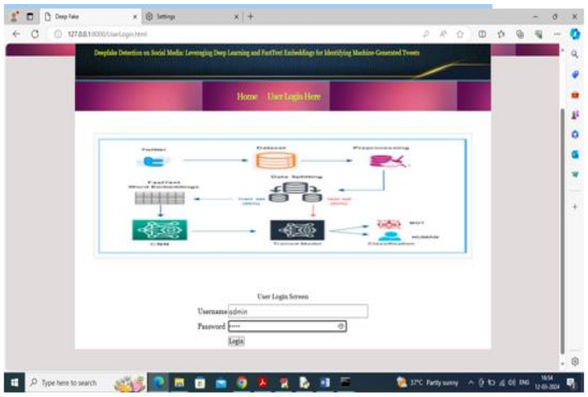
```
C:\Windows\system32\cmd.exe
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtyp
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
rstood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtyp
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
rstood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtyp
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
rstood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
WARNING:tensorflow:From C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\ba
_backend.py:4070: The name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.

WARNING:tensorflow:From C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\ba
_backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables in

(4143, 256)
System check identified no issues (0 silenced).

You have 15 unapplied migration(s). Your project may not work properly until you apply the migrations fo
 auth, contenttypes, sessions.
Run 'python manage.py migrate' to apply them.
March 12, 2024 - 16:50:43
Django version 2.1.7, using settings 'Deep.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-BREAK.
```

In above screen python server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below page



Deep Fake
127.0.0.1:8000/index.html
Deepfake Detection on Social Media: Leveraging Deep Learning and FastText Embeddings for Identifying Machine-Generated Tweets
Home
User Login Here
Deepfake Detection on Social Media: Leveraging Deep Learning and FastText Embeddings for Identifying Machine-Generated Tweets

In above screen click on 'User Login Here' link to get below page

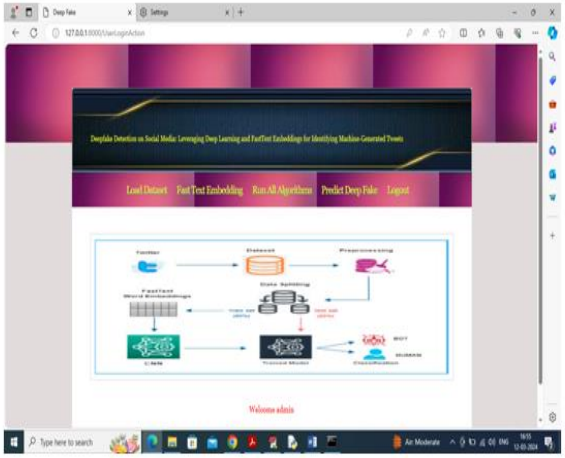


Deep Fake
127.0.0.1:8000/UserLogin.html
Deepfake Detection on Social Media: Leveraging Deep Learning and FastText Embeddings for Identifying Machine-Generated Tweets
Home
User Login Here
User Login Screen
Login

Username admin

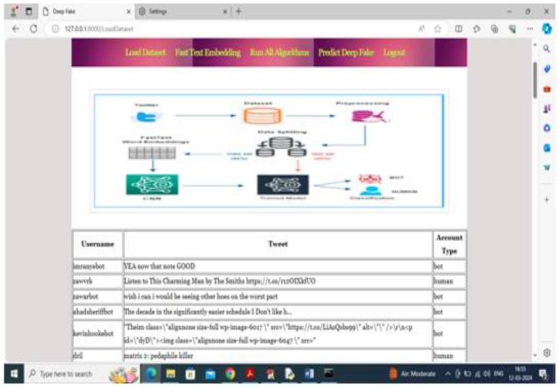
Password ••••

In above screen user is login and after login will get below page



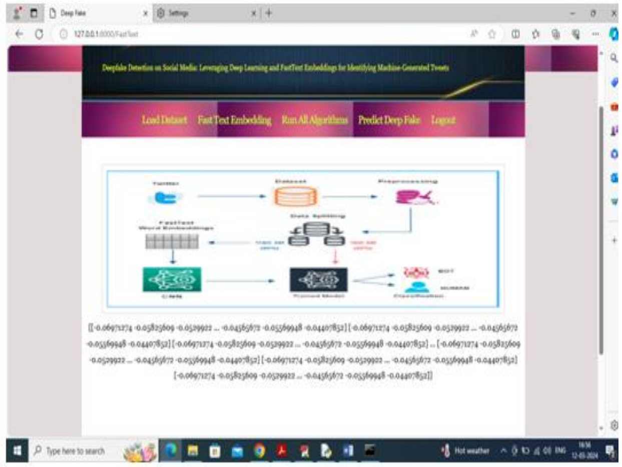
Deep Fake
127.0.0.1:8000/UserLoginAction
Deepfake Detection on Social Media: Leveraging Deep Learning and FastText Embeddings for Identifying Machine-Generated Tweets
Load Dataset
Fast Text Embedding
Run All Algorithms
Predict Deep Fake
Logout
Welcome admin

In above screen click on 'Load Dataset' link to load dataset and get below page



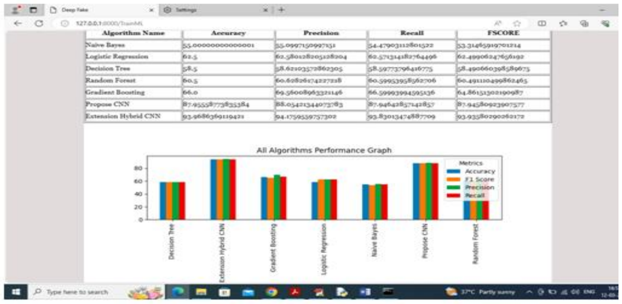
Username	Tweet	Account Type
imranyebot	YEA now that note GOOD	bot
zawvrk	Listen to This Charming Man by The Smiths https://t.co/r12OIXkfUO	human
zawarbot	wish i can i would be seeing other hoes on the worst part	bot
alhadsheriffbot	The decade in the significantly easier schedule I Don't like h...	bot
kevinhookebot	"Theim class=\"alignnone size-full wp-image-6017 \" src=\"https://t.co/LlAsQsbu99\" alt=\"\" />\r\n<p id=\"dyD\"><img class=\"alignnone size-full wp-image-6047 \" src="	bot
dril	matrix 2: pedaphile killer	human

Once you have the dataset loaded in the previous screen, go to the bottom of the page and click on the "Fast Text Embedding" option to turn all of the text into a numerical vector.



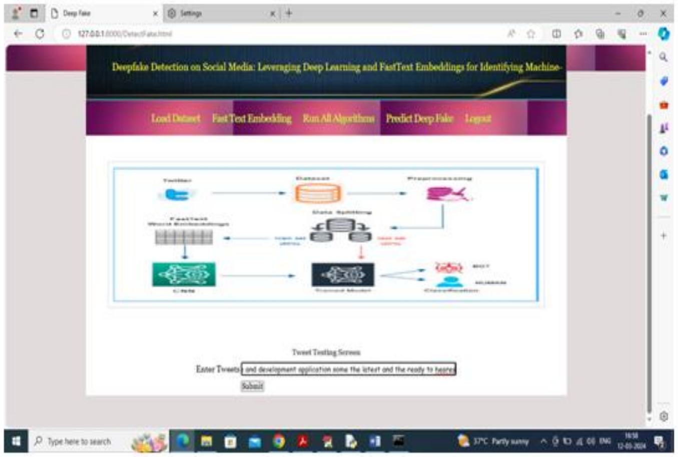
```
[[-0.06971274 -0.05825609 -0.0529922 ... -0.04565672 -0.05569948 -0.04407852] [-0.06971274 -0.05825609 -0.0529922 ... -0.04565672
-0.05569948 -0.04407852] [-0.06971274 -0.05825609 -0.0529922 ... -0.04565672 -0.05569948 -0.04407852] ... [-0.06971274 -0.05825609
-0.0529922 ... -0.04565672 -0.05569948 -0.04407852] [-0.06971274 -0.05825609 -0.0529922 ... -0.04565672 -0.05569948 -0.04407852]
[-0.06971274 -0.05825609 -0.0529922 ... -0.04565672 -0.05569948 -0.04407852]]
```

After converting all tweets to a numerical vector and showing a few numbers from it, you may train all of the algorithms by clicking the "Run All ML Algorithms" link, which will take you to the page below.



Algorithm Name	Accuracy	Precision	Recall	FSCORE
Naive Bayes	55.00000000000001	55.0997150997151	54.47903112801522	53.31465919701214
Logistic Regression	62.5	62.580128205128204	60.571314182764496	62.49906247656192
Decision Tree	58.5	58.62103572862305	58.59773796416775	58.490660398589675
Random Forest	60.5	60.60826174227218	60.59953958562706	60.491110499862465
Gradient Boosting	66.0	69.56008965321146	66.59993994595136	64.86151302190987
Propose CNN	87.95558773835384	88.05421344073783	87.94642857142857	87.94580923907577
Extension Hybrid CNN	93.9686369119421	94.1759539757302	93.83013474887709	93.93580290260172

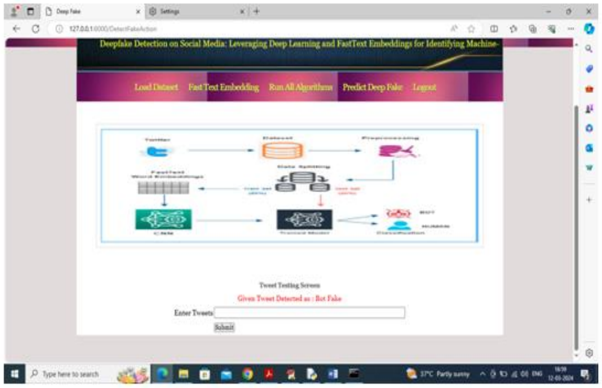
In Tables and graphs display the results of all methods; the top screen also shows that the proposed convolutional neural network (CNN) and the extended hybrid CNN achieved excellent accuracy. Next, go to the page below by clicking the "Predict Deep Fake" link.



Tweet Testing Screen

Enter Tweets: and development application some the latest and the ready to heares

You may use the example tweets provided in the 'test_tweets.txt' file, or you can input some tweet text in the text box above and hit the button to retrieve the values below.

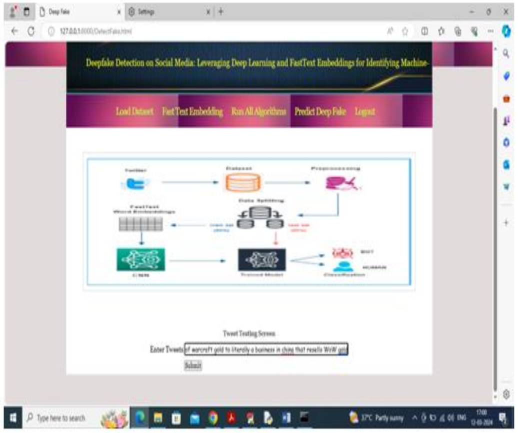


Tweet Testing Screen

Given Tweet Detected as : Bot Fake

Enter Tweets

The tweet labeled "Deep Bot" on the previous screen is really a bogus one that was propagated by a bot. Here's another example:

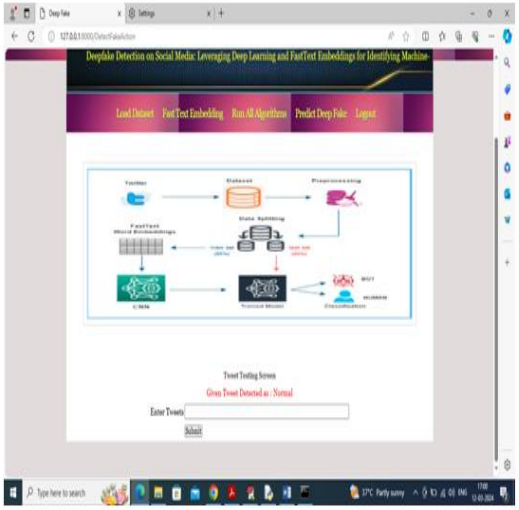


Deepfake Detection on Social Media: Leveraging Deep Learning and FastText Embeddings for Identifying Machine-

Tweet Testing Screen

Enter Tweets of warcraft gold to literally a business in china that resells WoW gold

In above screen entered some other tweet text and below is the output



Deepfake Detection on Social Media: Leveraging Deep Learning and FastText Embeddings for Identifying Machine-

Tweet Testing Screen

Given Tweet Detected as : Normal

Enter Tweets

The fact that a tweet marked as "normal" on the previous screen indicates that it was written by a human. Just like that, you may input a few tweets and get the results.

Conclusion

The objective of this research was to identify deep fakes, or automated tweets, by using deep learning techniques together with Fast Text embeddings. By using this strategy, we consistently distinguished between human-and computer-generated tweets.

Key findings of our research include:

Thanks to the extensive contextual data offered by Fast Text embeddings, our deep learning models performed much better. The results further support the idea that deep fake detection on social media platforms may be improved using domain-specific pre-trained embeddings.

The higher performance of transformer-based models, such as BERT, compared to traditional approaches in the **Deep Learning Model Performance** test proved their potential to grasp complex patterns in textual data. Deep fake detection is an example of a complex problem that highlights the need of using powerful neural networks. Effects on the Honesty of Social Media: We can significantly lessen the spread of misinformation and ensure the security of social media platforms by using these detecting systems. Social media companies should identify and label machine-generated material if they want to provide their users with more reliable information.

There are certain restrictions on our approach, notwithstanding the positive results we have witnessed. Due to their high processing requirements, models may struggle to keep up with the constantly evolving algorithms used to create text. There is also the persistent problem of adversarial methods that try to avoid detection mechanisms.

Future Work

Based on our findings, more research should focus on the following areas:

Enhanced Model Training: enhancing detection model performance across contexts and languages by training them on bigger and more diverse datasets. By creating optimized models for real-time identification, we can swiftly address the emergence of deep fake material on social media platforms.

Thirdly, we must ensure that detection systems are robust enough to withstand hostile attempts that aim to evade detection.

For a more comprehensive defense against the intricate structure of modern deep fakes, consider including multimodal detection into your arsenal. This strategy goes beyond text recognition alone and considers the interplay between text, pictures, and videos.

Lastly, although much has been achieved, deep fake technology is a dynamic field that needs ongoing

innovation and collaboration to keep up. Using state-of-the-art deep learning models and embeddings, such as Fast Text, we may develop more effective methods to safeguard the authenticity of social media information.
The study is presented in a comprehensive summary that highlights the significance of the results and lays the groundwork for future research.

Research papers pertaining to deep fake detection on social media platforms using deep learning and Fast Text embeddings should adequately mention all relevant foundational works, significant studies, and literature in their references section. The following is an example of a potential allusion:

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12. This list includes seminal works on word embeddings, transformer models, generative adversarial networks (GANs), and specific studies on detecting machine-generated text and fake news. Adjust the list based on the specific content and focus of your paper.