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FAKE CLASSIFIER

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ABSTRACT:

In the present generation, social media have emerged as an increasingly popular means for communication, information transfer, gathering and making new connections. Everybody's social life has been linked to social networking online. Daily, there is a dramatic increase in the number of people who use social media. These online media platforms have also been researched by scholars to see their effect on individuals. These platforms have significantly altered our way of living in society. This has, however, provided an opportunity for cyber threats like fake identities, false documents, etc. Therefore in this paper, we came up with an idea to build a fake classifier which we have been divided into three different modules in which the first module detects the fake profiles that are made on social networking sites, the second module detects fake news that is being spread by these particular accounts and third module consists of detecting the fake images posted by these accounts which are being photoshopped.

Our related work includes various algorithms that are being implemented in this project in broader aspects and we have used various machine learning algorithms to detect these accounts, news and images. The rapid growth in image generation and manipulation has now reached a point where it is raising questions about the consequences faced by the public. This not only undermines confidence in digital media content but also spreads false information and news. This paper investigates the reality of edited image content, false information and fake profiles as well as how hard it is to find them and how effective strategies can be used to do so.

Keywords: Social Networks, Fake profiles, Fake News Classification, Fake Image Detection, Neural Network, Random Forest

I. INTRODUCTION:

Data mining & analysis as well as its methods improve every day and even extends its uses. Such methods contribute to making choices, understanding the trends, forecasts and many others. Along with its automatic and powerful data processing capability, many realms like science, medicine, industry, manufacturing and much more embrace this innovation. In another hand, the current problems involved with data analysis are increased by diverse channels of connectivity and digitalization of records. Furthermore, data volumes are quickly expanded in multiple data warehouses and servers.

The proposed work demonstrates an effective implementation of the data mining and analysis process. Thus, the main field of research is the fake image, false news and fake profile detection. We have divided the fake classifier into three modules.

Module 1 is on fake profile detection. In today's modern society, everyone has become associated with an online social network. Growing online communication has altered drastically the quality of thinking. Internet mainstream media fundamental objective is to meet close acquaintances, maintain contact and communicate information, etc. Through social media sites, all these things have been simplified. The dissemination of misleading information at fast rate rises in the use of media platforms for fraudulent activities. Fake profiles are a big source of social media misinformation [21]. The extensive use of social networks has been a blessing for civilization. However, issues such as false accounts, sharing false propaganda, photographs and so on have evolved with the exponential development of the social networking web.

Module 2 is on fake news detection that shows the evolution of technology and the increasing spread of misinformation, this has become critical to develop automated mechanisms for detecting fake news. In this paper, we proposed a classifier, which conducts a binary classification on posts containing news from social networks and categorises them as "real" or "false." We used a learning algorithm in our methodology because it is highly successful in text categorization while still requiring less preparation time as each model would not have to be trained from scratch. Text pre-processing, tokenization, model estimation, and ensemble are the first phases in our method.

Module 3 is on fake images detection. Image manipulation is one of the most pressing issues in our digital age. Deep fake has shown how digital graphics and simulation techniques can be used to defame people by replacing their faces with those of other people. Faces are of particular concern to contemporary manipulation techniques for a variety of reasons. Human face reconstruction and tracking is a well-studied field in computer vision, which is the basis of these editing approaches. Second, faces are important in human communication because a person's face can highlight a message or even communicate a message on its own. Our challenge of image recognition is tackled by two strategies. First, external special signals would be embedded in the original images to detect forgery (e.g. digital watermarking). The sent image can then be checked to see whether it is genuine or manipulated. The invariant characteristics from the original images will be discovered using the second approach. We demonstrate in this paper that we can detect such manipulations automatically and accurately, outperforming human observers by a considerable margin. Advantages of the latest developments in profound education, especially the capacity to understand the increasingly capable CNNs from the convolutional neural network [20]. We found the solution to the detection problem using supervised learning to train the neural network. To achieve this, we created a large-scale dataset of manipulated images.

II. METHODOLOGY:

MODULE 1: FAKE PROFILE

Implementation is a method for classifying an element into a certain class using the experimental data collection used to train a classifier. We provide the classification system with such data to prepare it for the identification of multiple properties with the greatest possible precision. Throughout this research, we have used different classification algorithms, such as Neural Networks (NN), Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting, KNN, Naïve Bayes. [22]

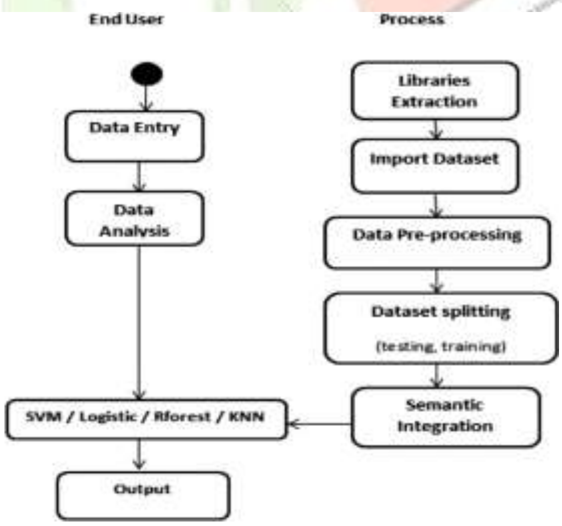


Fig. 1: Data pre-processing state chart [28]

- RANDOM FOREST: Random Forest is a common training algorithm for the supervised learning method. It is used for both classification and regression. Random Forest is a classification algorithm containing a variety of decision trees on subsets of the specified dataset and finds the average to increase the dataset's forecasting ability. The random forest collects the forecast within each tree, rather than depending on a single decision tree, and forecasts the final performance based on majority votes of decisions.
- SUPPORT VECTOR MACHINE OR SVM: SVM is one of the most efficient supervised learning algorithm which has utilization in both regression and classification problems. Even so, it is mostly used in machine learning for classification issues. The purpose of the SVM algorithm is to establish the best line or decision-

making boundary, allowing n-dimensional space to be divided into groups such that new data is conveniently categorised in future. These severe situation are called vectors of support and are therefore referred to as the Vector Machine help algorithms.

- GRADIENT BOOSTING: Gradient boosting is a regression and classification algorithm that generates a prediction model, a collection of weak prediction models, usually decision trees. The resulting algorithm is called gradient-boosted forests, which normally surpass random forests, while a decision-tree is the slow learner.
- KNN: Based on the supervised learning method, K-Nearest is one of the most simple machine learning algorithms. The new case/data and available cases conclude that the K-NN algorithm is identical and placed the new case into a group similar to those available. This makes it easy to classify new data into a suitable group with a KNN algorithm. For both regression and classification, the KNN algorithm can be used, but it is mainly used for the problems of classification.

A supervised learning algorithm based on Bayes and used for classification is the Naïve Bayes algorithm. It is primarily used for a high-dimensional testing dataset in text classification. The Naïve Bayes Classifier is one of the most basic and efficient classification algorithms that help to develop rapid learning models that can be predicted quickly. It is a classifier, meaning that it estimates based on an object's likelihood. Spam filtration, sentimental analysis and classification of papers are some common examples of the Naive Bayes algorithm.

Fig.2 System Architecture [22]

IMPLEMENTATION:

Our implementation consists of the following steps.

1. Data collection and data preparation.
2. Create deceptive profiles.
3. Fraudulent and true data validation.
4. Feature extraction.
5. Implement neural networks, random forest, etc.
6. Assess consistency outcomes, metrics for recall etc.

DATASET:

We used a dataset of fake and genuine profiles. Dataset consists of various attributes that can be useful for classification. These attributes include the number of friends, followers, number of likes etc. The dataset is divided into training and testing dataset. By using the training data the classification algorithms are trained and by using the testing data efficiency and results of these algorithms have been determined. 80% of the dataset is the training data and 20% for the testing data.

Table 1: Dataset Attributes of Training Model [29]

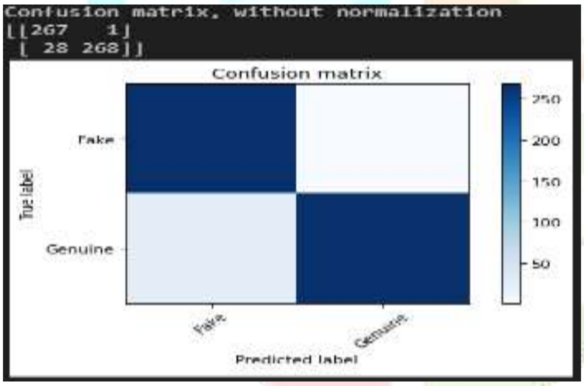
Attribute	Description
NAME	The name of the account holder
SCREENNAME	The pseudonym for the account
CREATED	The date the account was created
FOLLOWERS_COUNT	The number of followers for the account
FRIENDS_COUNT	The number of friends for the account
LANGUAGE	The language of the account holder
LISTED_COUNT	The number of groups the account belongs to
PROFILE_IMAGE	The profile image of the account
STATUS_COUNT	The number of tweets made by the account
LOCATION	The location of the account holder
TIMEZONE	The time zone of the account holder
UTC_OFFSET	The UTC offset, given the TIMEZONE
LATITIDE	The latitude where the last tweet was made
LONGITUDE	The longitude where the last tweet was made

EXPERIMENTAL RESULTS:

With the use of various classification algorithms, efficiencies have been determined and compared which helped in a good way in detecting fake accounts.

a. RANDOM FOREST :

Classification Accuracy on Test dataset: 0.9485815602836879



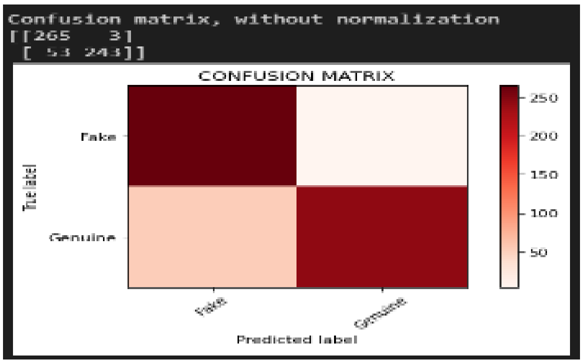
	precision	recall	f1-score	support
Fake	0.91	1.00	0.95	268
Genuine	1.00	0.91	0.95	296
accuracy			0.95	564
macro avg	0.95	0.95	0.95	564
weighted avg	0.95	0.95	0.95	564

Fig. 3.1 Confusion Matrix without Normalization

Fig. 3.2: Classification Accuracy

b. SVM :

Classification Accuracy on Test dataset: 0.900709219858156



	precision	recall	f1-score	support
Fake	0.83	0.99	0.90	268
Genuine	0.99	0.82	0.90	296
accuracy			0.90	564
macro avg	0.91	0.90	0.90	564
weighted avg	0.91	0.90	0.90	564

Fig. 4.1 Confusion Matrix without Normalization

Fig. 4.2: Classification Accuracy

c. GRADIENT BOOSTING :

Average Cross-Validation Score: 0.948979551613698

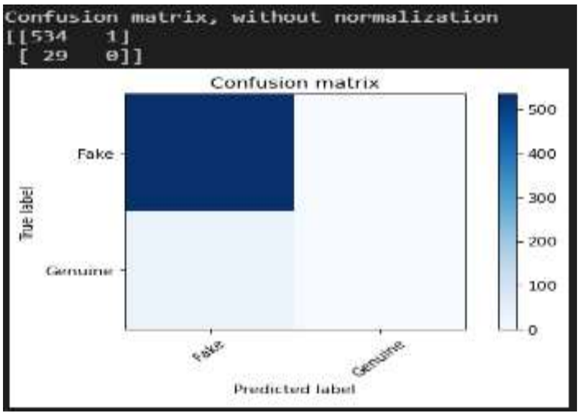


Fig.5.1 Confusion Matrix without Normalization

	precision	recall	f1-score	support
Fake	0.95	1.00	0.97	535
Genuine	0.00	0.00	0.00	29
accuracy			0.95	564
macro avg	0.47	0.50	0.49	564
weighted avg	0.90	0.95	0.92	564

Fig. 5.2: Classification Accuracy

d. NEURAL NETWORK :

Classification Accuracy on Test dataset: 0.934280639432

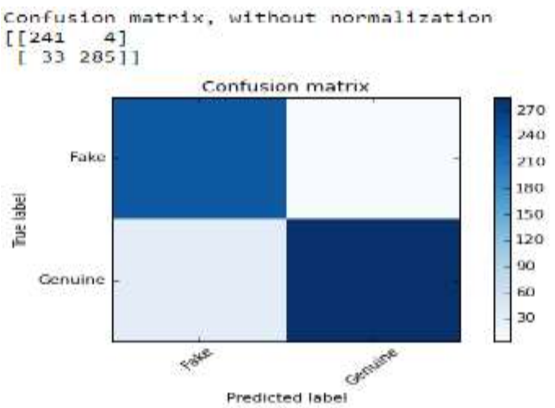


Fig. 6.1 Confusion Matrix without Normalization

	precision	recall	f1-score	support
Fake	0.88	0.98	0.93	245
Genuine	0.99	0.90	0.94	318
avg / total	0.94	0.93	0.93	563

Fig. 6.2: Classification Accuracy

MODULE 2: FAKE NEWS

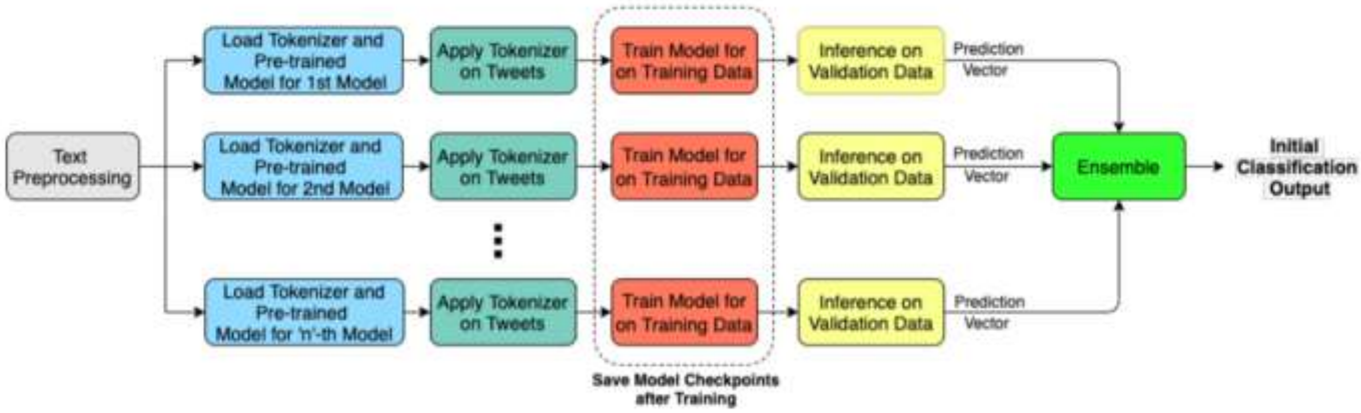


Fig. 7 Fake news identification initial process block diagram [5]

Attention towards fake news identification has grown in recent years, and there are several collective activities throughout this context, such as identifying false information spreaders, fake news challenge, and so on[2]. The mission of monitoring fake media spreaders through social media helps to recognize potential false information scrapers through social networks as the first phase towards stopping false propaganda from spreading between users.

IMPLEMENTATION:

News will be divided into one of two categories "true" or "false."

1. Pre-Processing: We experimented with various pre-processing pipelines using scikit-pipeline learns capabilities, in which the basic methods can be implemented
2. From removing words: English stop words are deleted from tweets while this step is used. Within this instance, NLTK provides the stop word dictionary.
3. Removal of the link: Hyperlinks links are deleted from online posts throughout this process. Known values are used to do this.
4. Lemmatization: Each step involves either lemmatization or stemming.
5. Stemming: Snowball Stemmer implementation, which is built on the Porter2 stemming algorithm, is used for stemming.
6. Words beginning begin @ (most widely included in Tweeting responses) are omitted throughout this step. Known values are also used to do this [8].

During the data gathering process, we adhere to the following fundamental rules:

- Just one aspect which is factored is textual based English content.
- Posts that were not in English aren't examined.

DATASET:

Dataset is gathered from several social media profiles, verifiable sources and personally checked the truthfulness within each tweet. The "true" information data were selected from authenticated communication channels on COVID-19, whereas the "false" versions were gathered from Twitter posts and blogs that purported on the COVID-19 as fake. The initial monitoring involves 10,700 stories for social networking sites, from which 37,505 are vocabulary terms and 51, 41 use the same generic term as and false news. It is classically equilibrated with 52.34% of legitimate news specimens and 47.66% of false samples.[6]

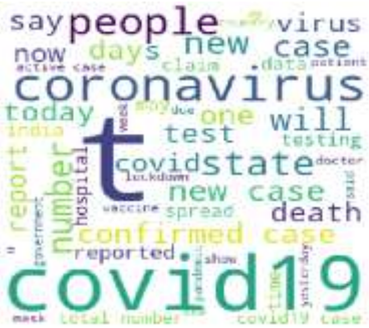


Fig.7.1: All Tweets

Fig. 7.2 Real News

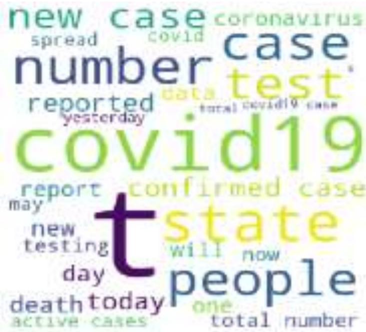


Fig. 7.3 Real News

Top 20 Words:

All Token Words	covid19,cases,coronavirus,new,people,tests,number, will,deaths,total,confirmed,reported,states,testing,covid19,health,covid,now,india ,one
Fake Words	coronavirus, Covid, people, will, new, trump, coronavirus, video, says, covid, vaccine, virus, president, hospital, covid, shows, India, pandemic, cases, claims
Real Words	covid, cases, new, tests, number, total, confirmed, reported, people, deaths, states, testing, now, health, report, coronavirus, will, state, covid,

DOMAIN NAME EXTRACTION:


```
OrderedDict([('twitter.com',
              {'fake_probability': 0.16226071103008205,
               'real_probability': 0.837739288969918,
               'total_mentions': 1097}),
             ('news.sky.com',
              {'fake_probability': 0.0,
               'real_probability': 1.0,
               'total_mentions': 259}),
             ('www.medscape.com',
              {'fake_probability': 0.0,
               'real_probability': 1.0,
               'total_mentions': 248}),
             ('www.thespoof.com',
              {'fake_probability': 1.0,
               'real_probability': 0.0,
               'total_mentions': 241}),
```

Fig. 8.1: Domain Name Extraction


```
twitter.com
www.thespoof.com
twitter.com
twitter.com
www.wandtv.com
t.co
www.thespoof.com
www.thelancet.com
t.co
www.politifact.com
investors.modernatx.com
t.co
twitter.com
```

Fig. 8.2: Domain Name Extracted

EXPERIMENTAL RESULTS:

Language models (LM) are widely included as feature extraction when dealing with textual information, contributing to freely available large-scale pre-trained language models (LMs). We use various transformer LMs, each with a feed-forward classifier trained on top of it. As previously mentioned, robust loss functions benefit in the improvement of neural network-based efficiency, particularly when dealing with chaotic datasets derived from social media.[1][3].

To improve CE symmetry, SCE adds a concept called reverse cross-entropy, which is inspired by the symmetric Kullback-Leibler divergence [6]. GCE takes advantage of the fact that mean absolute error is noise-resistant and CE performs very well difficult datasets.

On the test datasets, the effects of ML algorithms: Support vector machine has the highest Accuracy rate of 93.4 percent, led by Logistic Regression (LR) with an Accuracy rate of 92.7 percent. Decision Tree (DT) and Gradient Boost (GDBT), on the other hand, performed slightly worse, with F1-scores of 85.2 percent and 86.8 percent, overall. [8] The observations are also matched between two labels because the model was trained, validated, and tested on a balanced dataset.

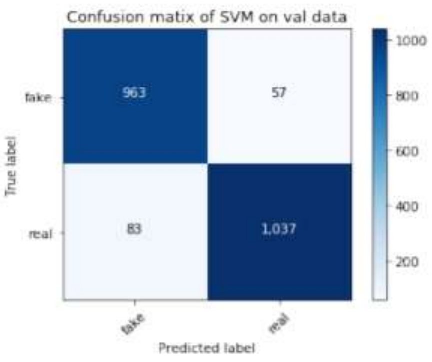


Fig. 9.1 Confusion Matrix without Normalization

```
SVM
val:
[[ 963   57]
 [  83 1037]]
              precision    recall  f1-score   support

        fake       0.92      0.94      0.93      1020
        real       0.95      0.93      0.94      1120

    accuracy                           0.93      2140
   macro avg       0.93      0.94      0.93      2140
weighted avg       0.93      0.93      0.93      2140

Accuracy :  0.9345794392523364
Precison :  0.9348008619335585
Recall :  0.9345794392523364
F1 :  0.9345519215989282
```

Fig. 9.2: Classification Accuracy

The confusion matrix of SVM projections on the training dataset is shown. The forecasts are often balanced between two labels since the model was trained, validated, and tested on a balanced dataset.

ANALYSIS OF ERRORS: We remove all the incorrectly classified and correctly classified instance created by the best performing scheme. We conducted a thorough examination of such instance to determine the trend in the prediction error as well as the verbal variations between those two types of cases. It has been discovered that the paradigm struggles most often in the media sphere, followed by competition and the business domain, among others. These cases are those that are currently "Legitimate," but expected to be "Fake," and those that are actually "Fake," but projected to be "Legitimate". The growing stage's architecture includes a set of mutual data encoding structures that encrypt contextual content, that can be optimised using recurrent neural networks or even a deep transformer consisting of stack self-attention levels.[07] Then encoder's specifications can be modified through all learning process. In our system, there are many two types of loss functions. The sentence-level loss, as well as the token-level losses, are also loss factors that are identical to BERT's loss functions.

MODULE 3: FAKE IMAGES

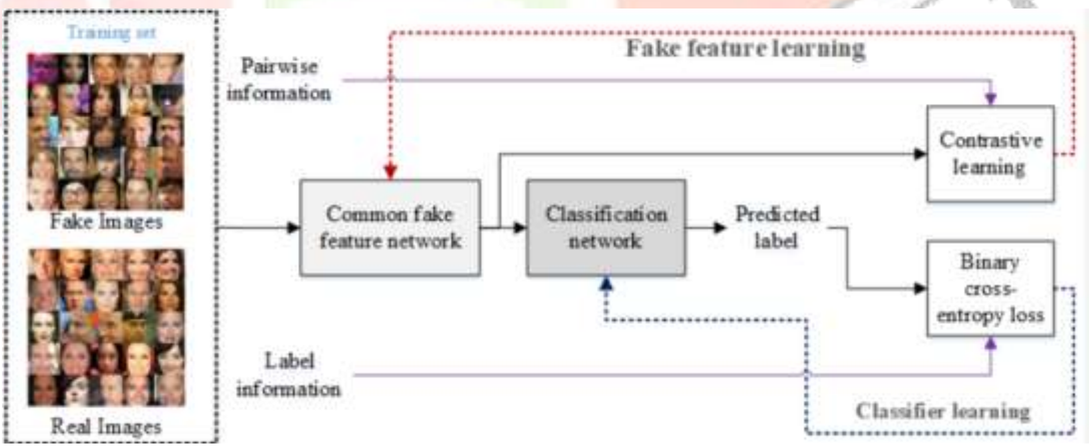


Fig. 10 Flowchart of the fake face detector[15]

The first approach necessitates the use of the original external signal to determine if it is fake or not. In most cases, having an original external signal (i.e. watermark) is borderline impossible with any picture obtained. The second approach, just looks for the image's inherent feature, such as an odd statistical property, to determine if it has been manipulated or not. There are many methods for determining tampered images by looking for inherent features in images. The inherent feature found by the forgery detection technique is sensor pattern noise. For JPEG formatted images, double compression cues are used as an inherent feature [16][17]. Traditional forgery detection techniques, on the other hand, have a hard time detecting images produced by computer edits because their image content is created directly by deep neural networks. As a result, there is no exceptionally statistical property in the inherent features of the received images, causing traditional forgery detection to missing the produced images. To address this shortcoming, we suggest a deep neural network-based approach called deep fake detection to detect fake images or other advanced networks effectively and efficiently. It is easier for a deep neural network classification to classify false and actual images with the collection of a broad training set [19]. Even so, the qualified classifier will fail in the detection of fraudulent images catalysed by today's technological processors, since it has not learned the discriminatory impact of modern frames. In general, it is hard to procure training pictures from all available image synthesisers. By integrating the contrasting failure into the network training system to ensure the success of the deep fake suggested, we appear to systematically acquire discriminating properties from collected testing pictures along with a dataset of images [15]. To be trained to classify similar subjects with the highest possible precision, we apply the classification model to the given dataset. In this research, we have measured its precision and effectiveness with classification models namely neural and deep fake algorithms.

IMPLEMENTATION:

1. Dataset collection.
2. Experiment settings.
3. Performance comparison.
4. Visualization of unrealistic details in fake images.

Fig. 11 Data pre-processing [18]

DATASET:

The dataset was taken from Kaggle, which contains a variety of false and actual image datasets. There are 70K phoney photographs and 70K actual images in the dataset. On the other hand, is trained on a specified dataset that includes both false and real image combinations.
The Kaggle dataset is used to obtain the training samples in this experiment. The photographs in the specified dataset include a wide range of pose variants and clutters, as well as a variety of identities and aligned face images. We chose 102,600 fake images at random from the false image pool. Finally, we have a set of training images as well as 2,000 test images, both genuine and false. Following that, the false and actual images extracted will be used to train the convolutional neural network and deep fake learning algorithms.

EXPERIMENTAL RESULTS:

CNN is made up of two basic components, namely pooling layers. For complicated picture recognition concerns, we use CNN. The CNN includes the idea of a hierarchy that is used to create a network like a funnel and eventually produces a linked layer with associated neurons and transferred output [24].Deep fake detection: Based deep learning detection involves approaches to decide if targeted content has also been engineered or synthetically produced by the use of multidisciplinary identification techniques.

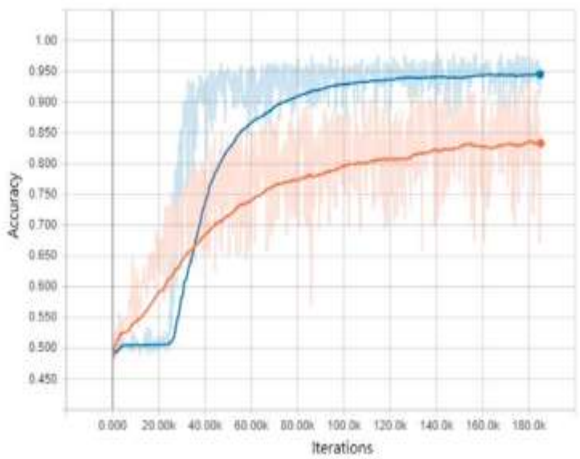
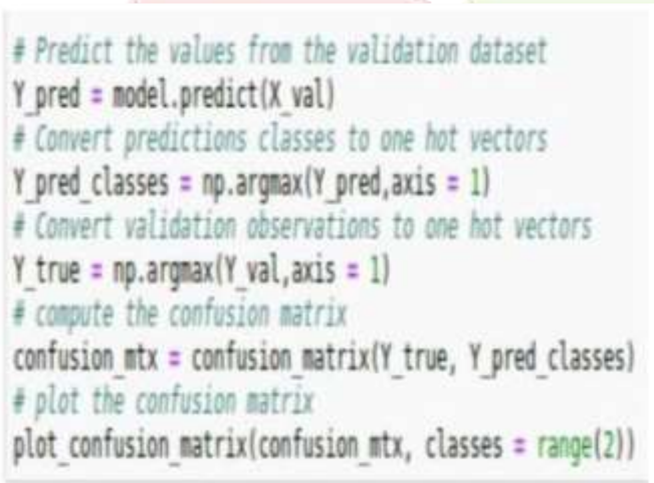


Fig. 12: Proposed deep fake Detection with (Blue line) and without (orange line) contrastive loss is compared.

Fig. 13: Training Accuracy on Data

We use pairwise information to guide dataset learning in two techniques to acquire the collectively discriminative feature task for this task. It has been established that feature learning is linked to classifier learning. It has been proven that Deep Fake's suggested technique is readily converged and achieves better performance. We can separate the fake images produced by one of the collection methods from the training pool to show the efficacy of the proposed deep fake detection. It has also been validated that the proposed Deep Fake outperforms other methods and that the proposed deep fake detection is more generalised and efficient than others in terms of performance. The solely supervised approach (i.e., the suggested method without contrastive loss) fails to capture the fake image's common features well. Deep fake detection, as suggested, makes it easier to extract the collectively discriminate feature for all types of fake images, resulting in improved performance [14].



```
# Predict the values from the validation dataset
Y_pred = model.predict(X_val)
# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_pred,axis = 1)
# Convert validation observations to one hot vectors
Y_true = np.argmax(Y_val,axis = 1)
# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
# plot the confusion matrix
plot_confusion_matrix(confusion_mtx, classes = range(2))
```

Fig.14 Classification accuracy on data sets

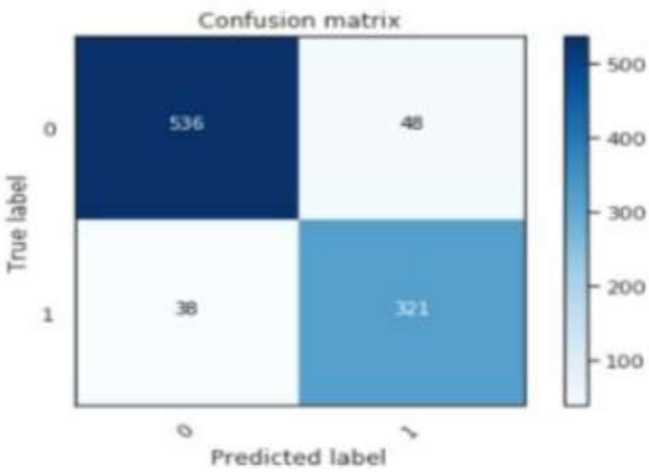


Fig. 15: Confusion matrix without normalization

III. CONCLUSION AND FUTURE WORK:

Our research broadens the interpretation of fake profiles, false information identification and fake images from either a single domain to a multi-domain approach, rendering it in a much more generalized and practical way. We test our proposed framework on training datasets of information from a range of systems [27].

Module 1 consists of the detection of fake accounts on social media platforms. The number of fraudsters is exponentially rising. As a result, numerous spam review detection techniques have been developed. Based on the papers examined, it is possible to infer that the majority of the study was created using classification methods such as SVM, decision tree, naive Bayesian, and random forest, KNN [25][26]. Statistics including such identification accuracy, performance, inaccurate predictions rate, F-Measure, Precision, and recall have been used to assess system effectiveness. Random forest and gradient boosting being classifier with very high efficiency of around 95%. Fake profile detection can be improved by applying NLP techniques to process the post and profile. In future work, we can also use the idea of attaching an aadhar card number while signing up for an account which will restrict the user to create a single account only.

In Module 2, we have identified false news. We gathered these messages from a variety of social media platforms then manually verify their accuracy. We have used a machine learning model to evaluate the built dataset and model it as a possible baseline. The SVM-based classification algorithm, which has an F1-score of 93 percent, surpasses all other machine learning algorithms. Future research may focus on gathering more data, stimulating the details by including the explanation for being actual alongside the names, and gathering data in several languages.

In Module 3, we have identified the manipulated images. We have sought to identify trends and emerging of distorted faces, in order to be able to surpass all current publicly available data sets. In the proposed methodology, we have gained an accuracy of 91% by using the deep fake detection technique. When new methods of deception appear every day, techniques must be developed to identify fake images with little or no formation evidence. We anticipate the datasets and standard will be foundations for more researches in the area and, in general in the field of forensic media content [13].

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