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Image Fake News Detection using Efficient NetB0 Model

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Abstract

Today, social networks have become a prominent source of news, significantly altering the way people obtain news from traditional media sources to social media. Alternatively, social media platforms have been plagued by unauthenticated and fake news in recent years. However, the rise of fake news on these platforms has become a challenging issue. Fake news dissemination, especially through visual content, poses a significant threat as people tend to share information in image format. Consequently, detecting and combating fake news has become crucial in the realm of social media. In this paper, we propose an approach to address the detection of fake image news. Our method incorporates the error level analysis (ELA) technique and the explicit convolutional neural network of the EfficientNet model. By converting the original image into an ELA image, it is possible to effectively highlight any manipulations or discrepancies within the image. The ELA image is further processed by the EfficientNet model, which captures distinctive features used to detect fake image news. Visual features extracted from the model are passed through a dense layer and a sigmoid function to predict the image type. To evaluate the efficacy of the proposed method, we conducted experiments using the CASIA 2.0 dataset, a widely adopted benchmark dataset for fake image detection. The experimental results demonstrate an accuracy rate of 96.11% for the CASIA dataset. The results outperform in terms of accuracy and computational efficiency, with a 6% increase in accuracy and a 5.2% improvement in the F-score compared with other similar methods.

Keywords: Fake News; EfficientNet; Fake Image; Social Media; Error Level Analysis.

1- Introduction

In the recent decade, It has greatly facilitated the rise of social media, the common way for people to get in touch with each other and share information. Social media has many positive characteristics, like ease of use, low cost, and 7x24 information accesses. Unfortunately, fake news has greatly increased on social platforms. The increasing rate of fake news has become one of the troubling issues since it can mislead people. Online fake news tends to be diverse and intrusive regarding topics, platforms, and styles. Fake news could have many negative impacts on individuals, business, and society. So, it is crucial to introduce and launch a system that could detect, explore and interpret fake news on social media. It is challenging to come up with a definition for “fake news” that could be accepted in general. According to Stanford University, fake news is “news articles that are intentionally and verifiably false and could mislead readers.” According to online Wikipedia, “a type of yellow journalism or propaganda that consists of deliberate misinformation or hoaxes spread through traditional print and broadcast media or online social media fake news[1],[2]. Social media is among the widely accepted platforms globally. Its characteristics are ease-of-use, rapid rate, and low cost, making it the most welcoming online platform for information sharing and social interaction [2],[3]. Today, more than two-thirds of American adults can access online news outlets. This increasing rate has made the Internet an ideal channel for fake news dissemination. Social media is the primary media for the propagation of fake news and, consequently, has been one of the prominent studied areas by industries and universities.

There are different social media platforms with distinctive features. The most popular ones are Facebook and Twitter, that have been found as the primary sources of fake news diffusion [4]. The significant difference between the two is that each post on Twitter, a microblogging site, is limited to 380 characters, while on Facebook, the limit is nearly 60,000 [5],[6].

The study in [7] indicates that 54% of users in industrial countries are worried about “what is real or fake” on social

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platforms. This concern has become more significant after the 2016 U.S. presidential election [8],[9] due to the influence of social media on political polarization and conflicts among the political parties during the campaign period [10]. Another instance is the surge in online fake news following the lookdown measures to curtail the spread of COVID-19 disease. A study recently reported a 25% increase in social media users following the global lockdown. According to a UNESCO report, "during this coronavirus pandemic. Hence, the WHO described all misinformation related to COVID-19 is often referred to as an "infodemic," which they defined as an overabundance of offline and online information[10],[3], [12]. To curtail this menace, many fact-checking online systems such as FactCheck.org have recently come up to verify political news; however, the practicability of these systems is restricted due to the numerous" types and formats of fake news that facilitate its dissemination on the social network [7], [13]

Fake images in the news play an outstanding part. Fake images are often used to provoke public anger and gather public opinion. When it shares in serious repercussions such as mass killings and religious conflicts, it has an even more devastating impact. Various software tools usually modify fake images. Since, they might severely affect people's thoughts. Adobe's state of the content survey revealed that engagement for posts with images is three times more destructive than posts with text only. As a result, the fake images inside fake news has been increased in social media in recent years. So, developing solutions to discover fake images and text content on social media platforms is a crucial task [3]. Moreover, online social data is time-sensible, meaning it appears in a real-time type and represents current events and issues. There is an urgent necessity for early detection approaches of fake news from the huge number of news articles published daily[14].

In this article, we propose an approach for fake image detection. The main advantages of the proposed method are as follow;

- Computational time: Using efficientNetB0 model helps us to learn image features with fewer parameters compared to other deep learning approaches. Consequently, it leads to find fake images in lower computational time, which is a crucial task in this area.
- Proper feature extraction: Additionally, converting the original image into an error-level analysis (ELA) image enables the model to capture the manipulated features that further lead to effectively detect fake images.
- Improved Efficiency: The results of the experiments on popular datasets indicate that the proposed approach outperforms the current state-of-the-art methods regarding precision, recall, and accuracy rates.

The rest of this paper is structured as follows: Section 2 presents some of the interesting related work on fake news detection. In section 3, we discuss the methodology. Section 4 present the dataset and experimental results. Finally, the conclusion and feature work are discussed in section 5.

2- Related Works

Social media has evolved into a crucial source of information and an integral aspect of our daily life. The majority of information on social media is in the form of photographs. Meanwhile, phony news events have been increasingly distributed on social media, leading to user confusion. The existing news verification techniques rely on features collected from the text content of tweets, whereas image features are frequently overlooked for verification of news. Fake news detection on photos has been the subject of few studies. The absence of training data is one of the drawbacks of using visual-based features. Building a human-labeled a fake news dataset is time-consuming and labor-intensive. As a result, creating a fake news dataset with images or videos to train is considerably a complex task. The following are the most recent studies on images in the field of fake news identification [15], [16], [17]

Dinesh Kumar Vishwakarma et al. [15]proposed an image-based fake news detection method. The method comprises four core components: "image text extraction, entity extractor, web processing, and processing unit." Initially, an algorithm was employed to extract the text region, and then the text was recovered from photos using optical character recognition (OCR). This way, results are fetched and further classified as reliable or unreliable connections. The high classification rate for this method is 85%. The dataset included the Google image/ Kaggle / Onion dataset. Zhiwei Jin et al. [18]proposed a method to detect fake images based on visual and statistical image features; the gain ratio method was used to remove redundant features. This procedure selects 11 elements from 42 features. Four classification models, SVM, LR, KStar, and RF, have been employed to train the method. The dataset comprises 50,287 tweets and 25,953 images of fake and actual news events on SinaWeibo. The highest accuracy rate was 83.6% using the Random Forest classifier.

Francesco et al. [19] proposed a fake image detection method that relies on GAN-based image to image translation; this method relies on the modern approaches taken from the image forensic. CNN has been used to train data. An accuracy rate of 89.03% was reported using 36302 image dataset.

D. Mangal [16] presented a Multi-Domain Visual Neural Network (MVNN) model for the detection of fake news; the model is comprised of "a frequency domain sub-network, a pixel domain sub-network, and a fusion sub-network." The fusion sub-network fuses the obtained feature vectors from the pixel and frequency domain sub-network through a fully connected layer; SoftMax activation is utilized to project the vector into either fake-news images or actual news. The Weibo dataset has been used in the experiments, and the accuracy rate reached to 84.6%.

Singh et al. [20] proposed an image-based fake news detection method. CNN with an attention mechanism is employed to detect fake images over the social network. The model uses high-pass filters to the kernel weights of the NN initialization. The two-dataset from Twitter and The approach described in [18], used a statistical and machine learning methods, suffers from efficiently fake news detection due to the challenge of identifying manipulated features in handcrafted image features. This limitation results in poor model generalization. As described in [22], the forensic methods have been employed to extract image features. However, these features are specific to particular manipulated features, whereas image fake news contents may contain multiple manipulated features. So, these features could not be ideal for effectively detecting image fake news. Previous studies [21] on image fake news detection have utilized other models, which effectively identify fake images based on general features but necessitate a significant number of training data.

CASIA 2.0 have been employed. The observed Accuracy rates were 83.2% and 94.7%, respectively.

Xue et al.[21]built a model called "Multi-Vision Fusion Neural Network" to detect pictures in fake news. To extract the image features from an image in pixel domain, the visual modal module is utilized. Meanwhile, the ELA is employed for feature extraction at the frequency domain. The input image features are extracted in the semantic detection phase using the pre-trained ResNet50. The physical features module extracts the physical part to recognize fake news images. All elements in the visual model are connected and passed to PCA to reduce the number of features. Then, the physical features module is combined with the visual feature one in an ensemble module for fake image detection.

To identify the final fake news image, XGBoost has been used. The datasets used in this approach are (D1) and (D2), while the accuracy rates reach to 93.41% and 88.53%, respectively.

However, to address these models' limitations, a new approach to image fake news detection has been proposed that uses the EfficientNetB0 model in this paper. The use of EfficientNetB0 results in higher accuracy with fewer parameters and shorter execution times, making it more efficient and faster option than other models.

3- Proposed Method

We propose a method to deal with the problem of image fake news identification in this paper.

The overall framework of the proposed method is displayed in fig1 and algorithm1.

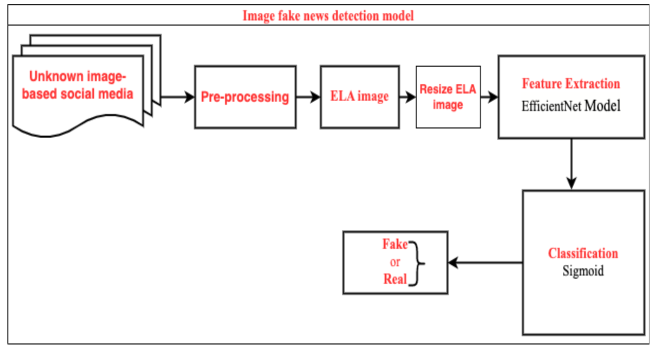

Fig. 1. The overall framework of the proposed method.

1. **Input**: (1) $\boldsymbol{I_R}$: Regular Image
2. $\boldsymbol{L_I}$: Image Label (Real/Fake)

3. **Output**: Prediction Image as Fake or Real

4. **Begin**
5. $\boldsymbol{I_{ELA}} \leftarrow$ Convert Regular Image To Error Level Analysis Image $(\boldsymbol{I_R})$
6. $\boldsymbol{I_S} \leftarrow$ Perform Error Level Analysis Image Resizer Method $(\boldsymbol{I_{ELA}})$
7. $\boldsymbol{F_{Efficient\ NetB0}} \leftarrow$ Extract Image Features Using EfficientNetB0 Framework $(\boldsymbol{I_S})$
8. $\boldsymbol{F_I} \leftarrow$ Process Image Features Using Dense Layers Framework $\left(\boldsymbol{F_{Efficient\ NetB0}}\right)$
9. $\boldsymbol{L_I} \leftarrow$ Regular Image Label PredictionMethod(F_I)
10. Optimize Image Fake Detection Results $(\boldsymbol{L_I})$
11. **end**

Algorithm1.The steps of the proposed Image Fake News Detection

3-1- Pre-Processing Stage

The main preprocessing operations are:

- The tiff image is removed. This is lossless image.
- Convert all the images into the RGB color space.
- Resizing the image: in this step, all the ELA images convert to (128*128 pixels).

3-2- Error Level Analysis Method

After the preprocessing stage, all the images are converted into ELA. ELA is a forensics technique. Created by [23]to draw attention to the areas where a picture has been compressed. It takes the feature of the lossy compression method of manipulated images to identify whether the image is tampered or not. Briefly, ELA is done as follows;

$$ELA_{im} = \left|org_{img} - rq_{img}\right| \quad (1)$$

Where $\mathrm{org}_{\mathrm{img}}$ the original image and $\mathrm{rq}_{\mathrm{img}}$ reduce quality image.

The difference between the two images is known as the error levels related to the original pixels. The error level indicates a number of changes that are directly connected with the compression loss. If the variation is minimal, the pixel has attained its local minimum for error at the specified error rate. However, if there is substantial alteration, the pixels are not in their local minimum and may be extraneous[24],[25],[26]. In our proposed method, the ELA algorithm is employed; accordingly, the re-saved version is compressed at a quality of 95%. Furthermore, the absolute variance between the quality and original images is found. The dissimilarities among images indicate the error levels associated with the initial pixels. To improve the performance of the model, we fine-tune the brightness of the images; a scale parameter has been used to fine-tune the results; the value of this parameter has been calculated as follow;

$$sca = 0.255|mix\ pixel \quad (2)$$

$$ela_{enh} = ELA_{im}\ .sca \quad (3)$$

where mix pixel is the maximum image pixel in ELA_{im}. Figure 2 shows the original image after converting into ELA image. Image a:

Image b:

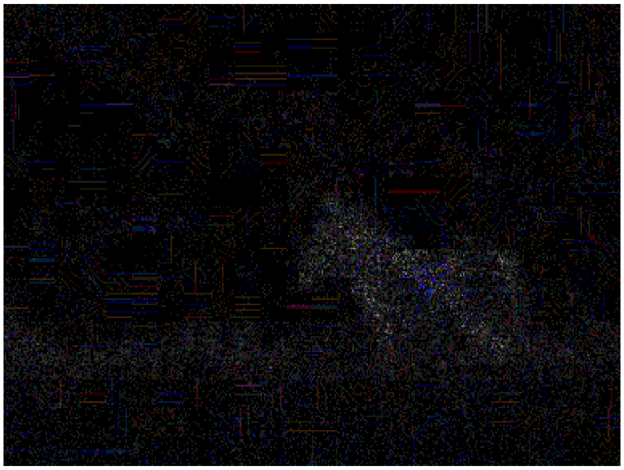

Fig. 2. a) The original image from Casia dataset and b) the image upon converting into ELA image.

3-3- Image Feature Learning

After the ELA images are produced, feature extraction is undertaken to establish feature vectors. In this paper, We have employed the EfficientNetB0 model belongs to the family EfficientNet from B0 to B7 in this study [27]; Accordingly, each variant of EfficientNet introduces different parameters as well as computational complexity time. Comparing them, EfficientNetB0 finds the lowest number of parameters while EfficientNetB7 needs the highest number of parameters for training.

Since one of the urgent necessities in fake news detection on social media is early and fast detection, we opted for EfficientNetB0, which uses fewest parameters. This allows for faster execution time and reduces computational resources without sacrificing the quality of the results. EfficientNetB0 has been designed using a novel scaling method that optimizes the model's depth, width, and resolution for the given computational resources. This approach has resulted in a model that can achieve high accuracy rate with fewer parameters, making it more efficient and faster than other deep learning models like ResNet, Inception, and VGG.

For feature extraction and added a global_average_pooling2d layer to reduce the overall number of parameters and hence limit overfitting. The EfficientNetB0 is a trained model on the ImageNet Dataset. To increase the model's efficiency, we re-trained the EfficientNetB0 model on our dataset, and the first layers from the EfficientNetB0 model pass to the global_average_pooling2d layer to reduce overfitting. The feature vector length (FS_{im}) is 1280 for the EfficientNetB0 model. Let

$$\mathrm{FS}_{im} = \emptyset_f(W_i\boldsymbol{F}_{\boldsymbol{EN}\mathrm{et}\boldsymbol{B0}}) \quad (4)$$

Where $\emptyset$ represents the activation function, Wi is the weight for each layer in EfficientNetB0, $\boldsymbol{F_{EN}}\text{et}\boldsymbol{_{B0}}$ is the output from the layer.

3-4- News Classification

The final stage in our proposal predicts the image into two classes as fake or real. For image feature extraction, we use the EfficientNetB0 model. Accordingly, the sigmoid function is used to ascertain whether an image is authentic or fake. The Relu (Rectifier Linear Units) is used in the dense layer as the activation function. We perform the predictor for image fake news by the sigmoid function as:

$$\tilde{p}_i = \text{FE}(\text{FS}_{im}, \emptyset_f). \quad (5)$$

Where $\emptyset_f$ indicates the parameters set of the sigmoid function, and FE is the mapping function.
Adam's optimizer has been utilized to optimize learning. Binary Cross Entropy is applied to calculate the loss function. $\tilde{p}_i = [\tilde{p}_1, \tilde{p}_2]$, hence $\tilde{p}_1$ denotes the probability of the given image as actual (0). $\tilde{p}_2$ indicates the likelihood of the image being fake (1).

4- Experimental Results & Analysis

We show the experiments conducted to assess the effectiveness of the proposed model. This section details the dataset, outcomes, and comparison with other related methods.

Fine-Tuning Given that social media has become a fundamental aspect of human daily life, detecting fake news on these platforms has become a crucial issue. Those methods used to spread fake news have evolved from text to images and even videos. In this study, we proposed a method to detect fake images using the EfficientNetB0 model, a member of the CNN family that is trained on the ImageNet dataset. In general, images play a critical role in news verification. In this regard, we have investigated on images to enhance fake news detection performance. The ELA method is employed with the EfficientNetB0 model. Furthermore, a global_average_pooling2d layer is added to reduce the number of parameters and to prevent overfitting. The EfficientNetB0 model has also been trained on our dataset, and weights were set for the EfficientNetB0 during the training process. We validate the effectiveness of feature learning on one of popular dataset, the CASAI. The proposed method achieves a validation accuracy rate of 96.11%. The model is designed to calculate the probability of the posts in the form of the entered image being real or fake. The results outperformed state-of-the-art methods on CASAI dataset, with a rate of approximately 6% in accuracy and 5.2% in the case of F-score rates.
In future, we intend to expand our method to social media datasets by extracting text from images and studying its impact on fake news detection.

4-1- Parameters

Transfer learning includes fine-tuning. We adjust our model that has previously undergone training on the ImageNet dataset. As mentioned, the images are initially converted into ELA images and further resized to 128*128 pixels. The EfficientNetB0 models have been used with pre-trained ImageNet weights (just the part CNN feature extraction, without prediction layers) by the EfficientNetB0 model and re-train parts of the network on our dataset. ImageNet dataset was frozen so that the weights of the ImageNet would not be affected by re-training on our dataset. After training the network and adjusting the parameters, we unfreeze the entire network. The last four layers (the top layer) related to the classification process in CNN from the network are removed and replaced with the proposed classification and activation function layers.
After re-training the network and extracting the features, we added a GlobalAveragePooling2D Layer with a dropout layer to eliminate the repetition in the features resulting from the re-training process and overfitting.
To make it fit with our classes, we have added two dense layers with a sigmoid function to predict whether the class type is fake or real.
The learning rate 1^{e-6} is set to warm up the FC. When applying fine-tuning, we allow the warm-up stage to train for 10 epochs based on our dataset. We will proceed to measure our network performance on the testing set after the warm-up phase. Table 1 describes the parameters used to fine-tuning model.

Table 1. Hyper parameter settings for EfficientNetB0

Hyperparameter	Values
Optimizer	Adam
Learning rate	10^{-6}
No. of dense layers	2
Dropout	0.5
Batch Size	32
Epochs	10
Total parameters	4,049,571
Trainable Parameters	4,007,548
Non- Trainable Parameters	42,023

4-2- Experimental Setup

The model was produced using a machine on Colab, employing the Keras library and the Google TensorFlow frame. To choose optimal hyperparameters, we have studied different batch sizes and dropout probabilities. The best results were achieved by utilizing the Adam optimizer with a learning rate of 10^{-4}; a batch size of 32, and training for 20 epochs. The hyperparameter values in this study are shown in table 2. Each experiment has been carried out randomly. Accordingly, the CASIA dataset is split into 80% as training and 20% as validation. The final findings were obtained when the ultimate level of accuracy was attained.

Table 2 . Hyperparameter values in the proposed model

Hyperparameter	Values
Optimizer	Adam
Learning rate	10^{-4}
Dropout	0.5
Batch Size	32
Epochs	20
Total params	168,129
Trainable Params	168,129
Non- Trainable Parameters	0

4-3- CASIA 2.0 Dataset

There are 12,616 images in the CASIA 2.0 dataset, where 5124 of them are manipulated, and the remaining 7492 images are legitimate. Copy-move and image-splicing techniques are used to manipulate the images. While performing tampering to the image, cropping and resizing are also done [28]. The number of CASIA images is shown in table 3.

Table 3 The statistics of CASIA V.2 dataset

Image type	Image size
Authentic – image	7200
Tamper – image	5123

4-4- Experimental Results

As mentioned in the previous section, the EfficientNetB0 model has been employed to learn the essential features, represented by the fewest number of parameters with high efficiency compared to the EfficientNetB1 model to EfficientNetB7. We have conducted our experiments on the CASIA dataset that contains images. The highest accuracy rate has been found as 96.11% in value. Four assessment measures have been used to evaluate the experimental results. Those are F1-score, Accuracy, Recall, and precision. Accuracy indicates how well the model classifies the images as real or fake.
The F-score measures the consistent mean of Precision and Recall; the performance of the proposed model, as shown in **Fig 3**, is found by four measures, Accuracy, Precision, Recall, and F-Score denoted as follows;

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

$$Recal = \frac{TP}{TP+FN} \quad (8)$$

$$F - score = \frac{2 * (Precision\ * Recall)}{(Precision\ + Recall)} \quad (9)$$

Where,
True Positive(TP) = Correctly classified.
False Positive(FP) = Incorrectly classified.
True Negative(TN) = Correctly Rejected.
False Negative(FN) = Incorrectly Rejected
AUC represented a level of separability. It indicates the model's capability to distinguish between classes. Although AUC has not been taken into comparison with other methods, it is significant for checking in classification problems; Fig 4 describes the confusion matrix of the proposed method on the CASIA data set. Fig 5 represents an ROC graph used to evaluate an imbalanced dataset, which is essential in binary classification. Table 4 displays a comparison between our proposed approach and other baseline methods. Refer to Table 4, [20]used the high pass filter with CNN to detect fake images. [29]Used the VGG19 model to detect fake images. MVNN[30] employed physical and semantic visual features to find fake news. In [31] utilized a CNN to extract features that help in the identification of fake news. As shown in Table 4, the proposed model can efficiently capture the modified characteristics in the fake image.

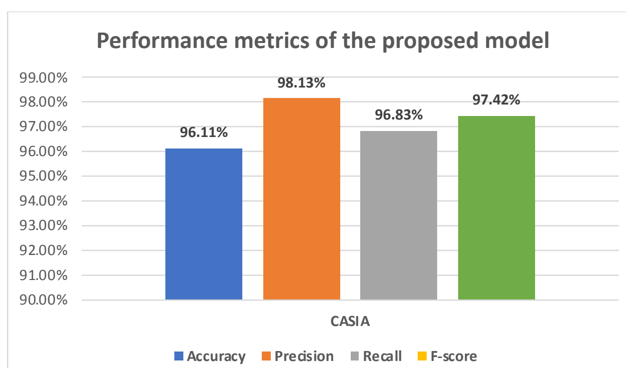

Fig. 3. The results of the proposed model's performance

Table 3 . Comparison of different models with our model

Method	Year	Accuracy	F-score
CNN [20]	2021	94.7%	95%
VGG19 [29]	2019	74.07%	79.11%
MVNN[30]	2019	89.12	94.53
CNN [31]	2017	74%	74.4%
Our proposed EfficientNetB0 model	2023	96.11%	97.42 %

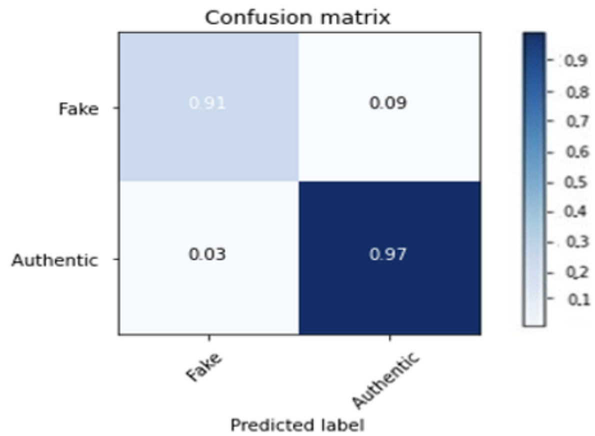

Fig. 4. Confusion matrix of the proposed method on CASIA 2.0 dataset

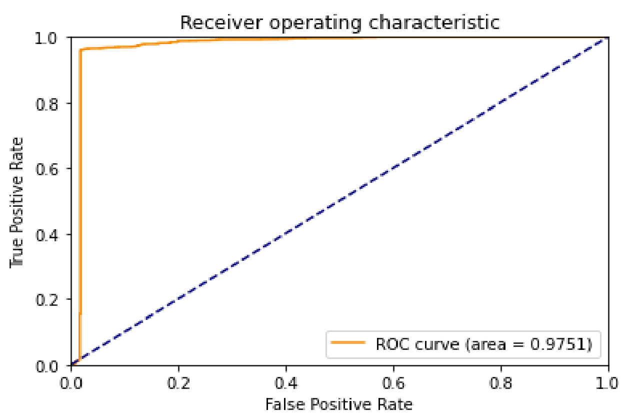

Fig. 5. AUROC curve on the CASIA 2.0 dataset

5- Conclusion

Given that social media has become a fundamental aspect of human daily life, detecting fake news on these platforms has become a crucial issue. Those methods used to spread fake news have evolved from text to images and even videos. In this study, we proposed a method to detect fake images using the EfficientNetB0 model, a member of the CNN family that is trained on the ImageNet dataset. In general, images play a critical role in news verification. In this regard, we have investigated on images to enhance fake news detection performance. The ELA method is employed with the EfficientNetB0 model. Furthermore, a global_average_pooling2d layer is added to reduce the number of parameters and to prevent overfitting. The EfficientNetB0 model has also been trained on our dataset, and weights were set for the EfficientNetB0 during the training process. We have validated the effectiveness of feature learning on one of popular dataset, the CASAI. The proposed method achieves a validation accuracy rate of 96.11%. The model is designed to calculate the probability of the posts in the form of the entered image being real or fake. The results outperformed state-of-the-art methods on CASAI dataset, with a rate of 6% in accuracy and 5.2% in the case of F-score rates.

In future, we intend to extend our method to social media datasets by extracting text from images and studying its impact on fake news detection. Furthermore, introducing an explanatory model is another further direction of our research.

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