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FusionNet: A Comprehensive Framework for Automated Deepfake Detection Using Multi-Modal Integration

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***Abstract*—Advances in deep generative models have led to the spread of deepfake media, which poses a serious danger to information authenticity, privacy, and trust in digital media forensics. In order to meet the increasing demand for reliable deepfake picture identification, this study uses the publicly accessible Kaggle Deepfake Dataset to investigate hybrid deep learning approaches. Initial experiments with standalone Keras models, including DenseNet121, RestNet50, Xception, NASNet-Mobile, VGG16, and InceptionV3, achieved accuracies ranging from 89% to 90% over 20 epochs. To push the boundaries of performance, we developed a novel hybrid model that concatenates feature maps extracted from DenseNet121 and DenseNet169. This method greatly improved classification performance, obtaining a 91.22% accuracy rate with high precision 90.82%, 94.37% recall, and 92.56% F1-score with error_rate 8.78%. Confusion matrices, classification reports, and ROC curves were used to thoroughly assess the model, which showed that it was effective at differentiating real photos from ones that had been altered, with an AUC value of 0.98. Our findings underscore the effectiveness of combining pre-trained CNN architectures for deepfake detection and contribute to the advancement of scalable, reliable solutions for safeguarding digital media integrity.**

***Index Terms*—Deepfake detection, Image classification, Deep Learning, Hybrid feature extraction, Convolutional Neural Network (CNN)**

I. Introduction

Deepfakes are fake media produced by artificial intelligence (AI) that covertly adds a person to a photo or video where they are not. In order to create realistic looks and expressions, neural networks are trained on vast amounts of human data. Although they have contributed to deepfakes, techniques such as GANs are not necessarily the main approach. AI and conventional graphics are used in modern systems to provide visually appealing outcomes [1].They are used to produce harmful media, such as phony pornography directed at celebrities and women. Deepfakes also undermine privacy and trust, increasing psychological abuse and suffering. Although there are certain valid uses, including cost-effective marketing, the risks frequently exceed the advantages [2]. Deep learning improves deepfake detection by using neural networks to identify patterns and subtle anomalies in digital media that indicate manipulation. Techniques like facial and body movement analysis, audio analysis (such as voice modulation and synthesis), and behavioral analysis help spot deepfakes by examining discrepancies in expressions, voice, and actions. Current advancements include the use of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for training models on large datasets and the integration of deepfake detection tools into social media platforms for real-time identification [3].The following are the research's contributions:

- suggested a hybrid framework that combines the DenseNet121 and DenseNet169 models to detect deepfakes.
- exceeded standalone models in terms of performance parameters, achieving 91.22% accuracy with a lower error_rate 0.0878.

The structure of the paper is as follows: Section II examines relevant research on deepfake identification and contemporary issues. The suggested technique and hybrid model are described in depth in Section III. The experimental design and execution are explained in Section IV. The results and analysis are presented in Section V, and the paper is concluded and future directions are discussed in Section VI.

II. Related Works

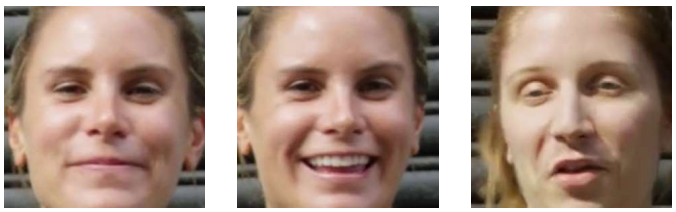
In order to unify the assessment of face alteration detection methods and to meet the growing concerns about the authenticity of digital material, Afchar et al. [4] present Meso-4 and MesoInception-4, two lightweight deep learning models for identifying face video forgeries, particularly Face2Face and Deepfake manipulations. The networks achieve remarkable detection rates of 98% and 95% for Deepfake and Face2Face forgeries, respectively, by concentrating on mesoscopic picture attributes and striking a balance between computational economy and performance. Although robustness to real-world video compression is highlighted by Afchar et al., results degrade at high compression settings. Ahmed et al. [5] offer a rationale-augmented convolutional neural network (CNN) for deepfake identification, which achieves an impressive 95.77% accuracy on the Kaggle DeepFake Video dataset. Using MATLAB, their approach focuses on effective real-time processing and addresses issues like facial reconstruction for security applications using webcams and surveillance cameras. Ahmed et al. show how reliable the model is and how it can be used to identify edited videos with little loss of data. Limitations, however, include the need for high-quality datasets for efficient performance and the computational cost of real-time implementation. Raza et al. [6] present a unique deepfake predictor (DFP) method that detects altered photos from the Kaggle dataset with 94% accuracy and 95% precision by combining VGG16 and convolutional neural network layers. Their analysis demonstrates how the suggested DFP model outperformed other approaches, including NAS-Net, Xception, MobileNet, and the conventional VGG16, which produced inferior performance measures. The model's shortcomings include its dependence on a small dataset (1081 actual and 960 fake photos) and its difficulty generalizing to big, diverse datasets, despite the fact that it shows promise for cybersecurity applications. Rössler et al. [7] introduced FaceForensics++, a large-scale benchmark dataset intended to address growing concerns about facial image modification and its societal repercussions. More than 1.8 million photos produced with four cutting-edge alteration techniques—Face2Face, FaceSwap, DeepFakes, and NeuralTextures—are included in this collection. The study's main contribution is the establishment of an automated benchmark for assessing manipulation detection techniques in practical settings, such as compression and different resolutions. With XceptionNet reaching the greatest accuracy of 99.26% on raw videos, the authors also showed how utilizing domain-specific knowledge greatly improves the performance of deep learning models. The paper does point out several drawbacks, though, such as difficulties identifying GAN-based manipulations like NeuralTextures, where model performance degrades under severe compression.

III. Methodology

To detect deepfake photos with high accuracy, the suggested architecture uses a hybrid deep learning technique [8]. In order to improve classification results, this work improves the integration of many pre-trained deep learning models and assesses their performance.

A. Dataset

We used the publicly accessible Kaggle Deepfake Dataset [9], which included 11,407 photos divided into real and deepfake categories, for our investigation. The dataset was initially split into an 80:20 ratio, creating separate training and testing sets. Subsequently, 80% of the training data was further divided into training and validation subsets using an 80:20 ratio. A visual representation of the data set sample is provided in Fig. 1.



(a) Image 1 (b) Image 2 (c) Image 3

Fig. 1: Some Sample of Dataset

B. Data Preprocessing & Augmentation

In order to ensure uniformity and improve the stability of the training process, normalization was used during the preprocessing step to scale the pixel values of all images within the range [0, 1]. A number of data augmentation strategies were used to increase the model's ability to generalize to fresh and untested data. TABLE I illustrates the augmentation techniques implemented in this study.

TABLE I: Transformation for data augmentation

Technique	Value
Rotation Range	20 degrees
Width Shift Range	0.2
Height Shift Range	0.2
Shear Range	0.2
Zoom Range	0.2
Horizontal Flip	True
Vertical Flip	True

C. Training Models

1) DenseNet121: A pre-trained version of the model, initialized with ImageNet weights, was adjusted for the deepfake detection task in order to maximize DenseNet121's performance. Custom layers designed for binary classification were used in place of the original architecture's completely connected layers. These comprised a global average pooling layer, dense layers with dropout regularization to avoid overfitting, and ReLU activation. In order to speed up and stabilize the training process, batch normalization was added. Lastly, to produce probability scores for binary classification, a thick layer with a sigmoid activation function was included.

2) DenseNet169: The same method was used to refine DenseNet169 for deepfake detection. This model sought to extract more complicated features from the dataset by utilizing its deeper architecture. In order to improve performance and generalization, the fully connected layers were adjusted to fit the classification job, utilizing batch normalization, dropout, and dense layers.

3) Proposed Fusion Model: By combining the features taken from DenseNet121 and DenseNet169, a fusion model was produced that capitalized on the complementing advantages of both architectures.The fusion model's robustness and classification accuracy were enhanced by this fusion strategy, which enabled it to identify a wider variety of patterns in the dataset. Figure 2 illustrates how the fusion structure was created by combining two pretrained models.

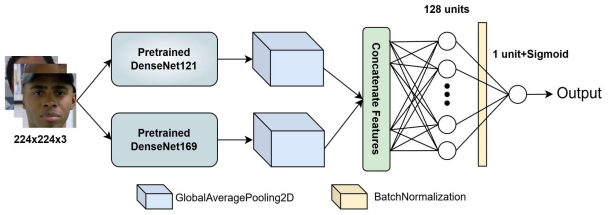


Fig. 2: Feature-level fusion framework combining DenseNet121 and DenseNet169 models for enhanced classification.

IV. Experimental Setup and Implementation

The study was conducted in a Kaggle environment utilizing a GPU accelerator with 30GB of RAM, and Python was the primary programming language employed for coding. To determine which combination of hyperparameters produces the greatest results on a validation set, we methodically explored a variety of values in our study.The chosen hyperparameters used in our investigation are displayed in Table II.

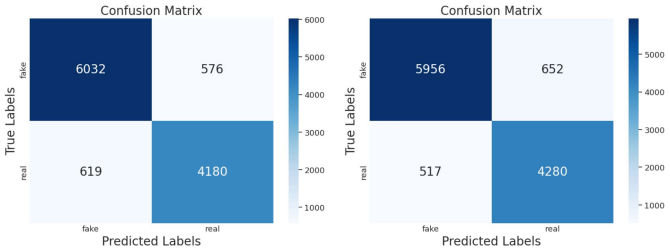
TABLE II: Parameters used in the pre-trained deep learning models

Parameter	Value
batch size	32
number of epochs	20
optimizer	adam
learning rate	0.0001
output classifier layer	sigmoid
activation function	relu

V. Experimental Results and Analysis

To evaluate the effectiveness of the proposed models, experiments were conducted using the enriched dataset. Together with the results of the separate models, DenseNet121 and DenseNet169, Table III also shows the results of some pretrained models.

The findings demonstrate that the proposed model outperformed the individual models, achieving the highest accuracy and F1-score. Even though DenseNet121 and DenseNet169 performed well in classification when used separately.The confusion matrix, displayed in Fig.3, illustrates the classification capabilities of individual models, whereas Fig.4 of the proposed model distinguishes between deepfake and real images.



(a) For DenseNet121 model (b) For DenseNet169 model

Fig. 3: Confusion Matrix of both model

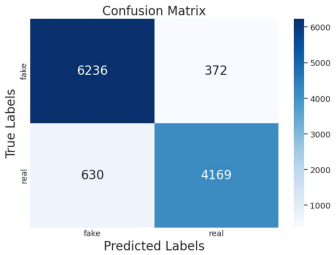
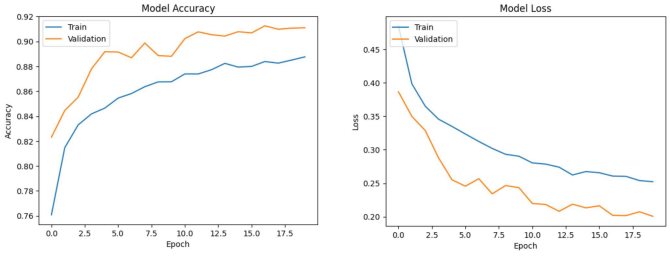


Fig. 4: Confusion Matrix of proposed fusion model

The accuracy and loss curves in Fig. 5 show how the proposed model converged throughout training and validation. Furthermore, Table IV shows the Classification Report.



(a) Accuracy Curve (b) Loss Curve

Fig. 5: Accuracy and Loss Curve for Proposed Model.

TABLE III: Experimental Results

Model	Accuracy(%)	Precision(%)	Recall(%)	F1_Score(%)	Error_rate	G_mean(%)	AUC
DenseNet121	89.53	90.69	91.28	90.99	0.1048	89.17	0.97
DenseNet169	89.75	**92.01**	90.13	91.06	0.1025	89.68	0.97
ResNet50	58.01	57.99	**99.83**	73.37	0.4199	6.45	0.71
Xception	88.70	89.40	91.40	90.40	0.1130	88.10	0.96
VGG16	85.25	82.26	95.05	88.19	0.1475	82.59	0.94
VGG19	80.85	88.05	77.47	82.46	0.1915	81.28	0.90
NASNetMobile	82.73	80.31	92.99	86.19	0.1727	79.87	0.92
InceptionV3	87.88	87.92	87.13	87.44	0.1212	86.96	0.95
DenseNet121+DenseNet169	**91.22**	90.82	94.37	**92.56**	**0.0878**	**90.54**	**0.98**

TABLE IV: Classification Report of the Proposed Model

	Precision	Recall	F1-Score	Support
real	0.91	0.94	0.93	6608
fake	0.92	0.87	0.89	4799
Accuracy			0.91	11407
macro avg	0.91	0.91	0.91	11407
weighted avg	0.91	0.91	0.91	11407

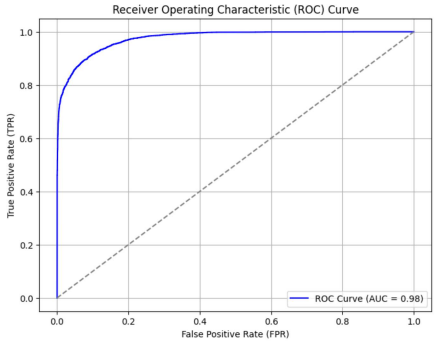


Fig. 6: ROC Curve of Proposed Model

The findings show that the proposed model performs better than the individual models on a number of evaluation parameters.Table IV displays a comprehensive classification report for the proposed model.And Fig. 6 displays a ROC curve of the proposed model.

VI. Conclusion & Future Work

When compared to separate models, the proposed fusion model—which combines DenseNet121 and DenseNet169—achieved a high accuracy of 91% and improved precision, recall, and F1 score. These findings highlight how combining different architectures' feature extraction capabilities might improve classification performance. Future research could explore several promising avenues, including the application of explainable AI techniques [10] to enhance model interpretability and reliability and the design of lightweight convolutional neural network (CNN) architectures to improve scalability and real-time efficiency. The proposed framework has the potential to greatly progress the field of deepfake detection by tackling these issues, making it more dependable, effective, and accessible for a variety of applications.

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