EfficientNet-B6 – Based Fake and Propaganda Image Detection using AGSK Optimization

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Abstract *- Deepfake technology is a major threat to online security that allows for the production of highly realistic manipulated videos and images. Current detection methods tend to have difficulty generalizing because of deepfake generation techniques keep changing. In order to tackle this problem, we introduce an enhanced deepfake detection system combining EfficientNet-B6 for stable feature extraction and Automated Adaptive Gaining Sharing Knowledge (AGSK) for adaptive hyperparameter tuning. The system is preprocessed by applying techniques like image normalization, resizing, data augmentation, and noise reduction to improve input quality. Capsule Networks are also utilized to preserve spatial hierarchies to enhance the classification accuracy. The suggested model is trained on a diverse set of data and achieves 99% training accuracy and 96% testing accuracy compared to traditional CNN-based models. This architecture provides a scalable and effective real-time deepfake detection method applicable in digital forensics, media authentication, and social media content moderation to prevent misinformation and confirm media authenticity.*

Keywords*: Deepfake detection, EfficientNet-B6, AGSK optimization, CapsuleNet, Hyperparameter tuning,Fake image classification, Machine learning.*

1. Introduction

Deepfake technology based on deep learning has been a cause of concern because it can lead to misinformation, fraud, and privacy breaches. Thanks to advances in artificial intelligence, attackers can now create hyper-realistic artificial images and videos that fool people, organizations, and governments alike. The problem with identifying deepfakes lies in how they can convincingly simulate authentic facial expressions, voice patterns, and environmental details at high fidelity, making them harder to identify as inauthentic content.

The spread of deepfake material has had significant implications across media, politics, cybersecurity, and social media. Synthetic media-generated fake news, identity theft, and social engineering attacks are increasingly being performed with the help of AI-generated deepfakes. Such attacks challenge digital information credibility, necessitating advanced detection mechanisms that can match the fast-paced evolution of deepfake generation tools.

The conventional deepfake detection techniques are mainly based on handcrafted features and heuristic-based techniques, including finding inconsistencies in face movements, illumination, and texture. Although the techniques have proven to be beneficial, they do not perform well with the ever-changing deepfake methods that use more sophisticated AI models, thus lowering the accuracy of detection. Additionally, rule-based techniques tend to be hindered by the use of predetermined features, thus failing to deal with new deepfake methods.

Deep learning models have become popular in deepfake detection recently because they can learn complex feature representations directly from data. However, current models suffer from several issues, such as high computational complexity, overfitting on particular datasets, and the inability to capture hierarchical relationships between features in images. With the evolution of deepfake methods, traditional machine learning models tend to be outdated, making adaptive and scalable detection mechanisms inevitable.

To overcome these difficulties, this research introduces a new method combining EfficientNet-B6 with AGSK optimization to enhance deepfake detection efficiency and effectiveness. EfficientNet-B6, a high-performance deep learning architecture, offers hierarchical feature extraction with optimized computation resource utilization through its compound scaling mechanism. Furthermore, AGSK optimizes hyperparameters like learning rate, batch size, and convolutional layers dynamically, further enhancing learning performance and flexibility. The integration of these approaches yields a strong and effective deepfake detection system, which can identify manipulated images with high accuracy and low computational cost.

By combining the strengths of EfficientNet-B6 and AGSK, this study is a part of the continuous fight against deepfake-based misinformation. The introduced model seeks to offer a high-accuracy, scalable solution for detecting manipulated images, opening doors to more trustworthy digital media verification and cybersecurity solutions.

2. Literature Survey

A number of approaches have been investigated for deepfake detection, each with its advantages and disadvantages:

DNN-based Face Recognition (Zhu et al., 2020): Deep neural network-based face recognition algorithms attained high accuracy in detecting manipulated images by examining facial patterns and discrepancies. They took a long time to train, used a lot of computational power, and were prone to overfitting when tested on unseen data, limiting their real-world applicability.

CNN and GAN Models (Wang et al., 2020): Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) enhanced the synthesis of fake images, rendering detection more difficult. CNNs exhibited robust feature extraction ability, but they tended to struggle with generalization across various deepfake styles. GAN-based detection models could identify manipulated artifacts, but they were susceptible to adversarial attacks, where more sophisticated deepfake algorithms could evade detection.

ResNet-based Forensic Detection (Yang et al., 2021): ResNet models were utilized for forensic examination of edited images, successfully detecting deepfake traces by identifying pixel-level inconsistencies. Although they successfully highlighted pixel-level inconsistencies that indicated deepfakes, their computational complexity and memory requirements made them not feasible for scalable or real-time scenarios, where their application was restricted in dynamic digital spaces.

CapsuleNet Approaches (Ryu & Jang, 2022): Capsule Networks exhibited better performance in spatial relationship modeling in images and thus were highly efficient in deepfake detection. CapsuleNet maintained positional and hierarchical information as opposed to regular CNNs, which improved feature representation. Its slow convergence rate and computational complexity became bottlenecks in real large-scale application, and more optimization methods were required.

Even with these developments, current deepfake detection models have limitations in terms of computational cost, flexibility, and resilience to changing deepfake methods. Our model improves upon these methods through the use of AGSK for hyperparameter adjustment and EfficientNet-B6 for optimal feature extraction. The combination of these advanced methods leads to a more computationally effective, flexible, and scalable deepfake detection system that solves major problems in real-world applications.

3. Proposed Framework

The suggested deepfake detection framework is organized into a number of principal steps to improve detection performance at an affordable computational cost. The main elements are pre-processing, feature extraction, and deepfake classification with EfficientNet-B6 and the AGSK optimization algorithm.

3.1. Pre-Processing

Data preprocessing is critical in improving the accuracy and efficiency of deepfake detection models. Correct preprocessing guarantees that input images are clean, uniform, and optimized for feature extraction. The preprocessing pipeline for this research includes the following steps:

Image Normalization: Pixel values are scaled to **[0,1]** or **[-1,1]**, ensuring brightness and contrast consistency.

Resizing: To ensure compatibility with the deep learning model, all input images are resized to **300×300 pixels** while preserving the aspect ratio. **Bilinear interpolation** is applied during resizing to retain important structural details. This step reduces computational complexity while ensuring uniformity in the dataset.

Data Augmentation: Rotation (**±20°**), horizontal flipping, brightness adjustment (**±15%**), and Gaussian noise addition expand dataset diversity and prevent overfitting.

Noise Reduction: Median filtering removes salt-and-pepper noise, while bilateral filtering preserves edges while reducing distortions.

Normalization & Scaling: To ensure better model convergence, extracted feature values are normalized using **Z-score normalization**, which standardizes values by subtracting the mean and dividing by the standard deviation. **Histogram equalization** is applied to improve contrast, making deepfake artifacts more distinguishable..

3.2. Feature Extraction

Feature extraction is an important process in deepfake detection that allows models to extract distinguishing features between real and tampered images. Deepfake images tend to carry minute but visible differences in color, texture, and spatial geometry, and therefore feature extraction plays a key role in enhancing the accuracy of classification. Capsule Networks (CapsuleNet) are popular choices for feature extraction because they are capable of maintaining spatial hierarchies in image data. In contrast to the conventional Convolutional Neural Networks (CNNs), which have difficulty with positional changes, CapsuleNet utilizes vectorized neuron activations that retain orientation, scale, and position information. The network applies a dynamic routing algorithm to decide on feature significance so that the learned features reflect structural variations between genuine and forged images. Another popular approach is EfficientNet-B6, an advanced CNN design that is optimized for feature extraction, applying compound scaling to balance network depth, width, and resolution, allowing efficient learning of deepfake patterns at a reduced computational cost. Squeeze-and-excitation mechanisms built into the model enhance feature selection by dynamically recalibrating channel-wise feature maps, enhancing the ability to detect manipulated regions. Texture and frequency domain analysis also have a crucial role in feature extraction wherein high-pass filtering methods like Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) are used to unearth high-frequency details that expose artifacts caused by deepfake creation. These techniques assist in identifying deepfakes by observing inconsistencies in frequency distributions and compression patterns. In addition, edge and boundary detection algorithms like Canny Edge Detection and Laplacian filtering refine feature extraction by identifying irregularities in contours and texture. Deepfakes tend to have unnatural blurring at facial edges, which makes edge-based feature extraction pivotal in forensic image analysis. For improving computational efficiency, the extracted features are applied with dimensionality reduction methods like Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE), which remove redundant data while maintaining essential feature representations. The Adaptive Gaining Sharing Knowledge (AGSK) algorithm also improves feature selection by adjusting hyperparameters dynamically, so that only the most important features are preserved for classification. By utilizing advanced methods like CapsuleNet, EfficientNet-B6, frequency domain analysis, and edge detection, deepfake detection models can be made more robust and accurate. In addition, dimensionality reduction and AGSK-based optimization improve computational efficiency, making deepfake detection more effective and scalable for practical uses.

Technique	**Description**	**Advantages**
ELA	Detects inconsistencies in compression.	Highlights manipulated regions.
JPEG Analysis	Identifies compression artifacts.	Useful in forensic analysis.
Noise Reduction	Removes noise and artifacts.	Enhances feature extraction.
Image Normalization	Standardizes pixel values.	Improves image consistency.
Data Augmentation	Increases dataset variability.	Prevents overfitting.
Resizing & Cropping	Adjusts image dimensions.	Reduces computational load.
Edge Analysis	Detects AI-generated anomalies.	Aids forensic verification.

3.3 Deepfake Detection

This section comprises the deepfake detection model using an automated Adaptive Gaining Sharing Knowledge (AGSK) optimization algorithm with the EfficientNet-B6 architecture. The proposed framework consists of multiple phases, including feature extraction, hyperparameter tuning, and classification, ensuring robust detection of manipulated images.

3.3.1 EfficientNet-B6 Architecture

EfficientNet-B6 is a convolutional neural network (CNN) that utilizes compound scaling to balance model depth, width, and resolution for optimal performance. Unlike traditional CNN architectures, which scale parameters arbitrarily, EfficientNet-B6 optimally allocates computational resources, improving feature extraction while reducing training complexity. The model incorporates squeeze-and-excitation networks to enhance channel-wise feature selection, effectively identifying fine-grained differences between real and deepfake images. Additionally, EfficientNet-B6 extracts hierarchical features from manipulated images, making it well-suited for deepfake detection.

3.3.2 Adaptive Gaining Sharing Knowledge (AGSK) Algorithm

The AGSK algorithm optimizes model hyperparameters dynamically, improving training efficiency and detection accuracy. This evolutionary optimization algorithm mimics human learning processes, refining parameters in a structured manner.

3.3.2.1 Junior Gaining and Sharing Phase

In this phase, initial hyperparameters are selected based on a limited dataset. The model iteratively refines its learning process by adjusting parameters such as learning rate, dropout, and convolutional layer configurations. This stage resembles early-stage human knowledge acquisition from a small, controlled environment.

The population initialization is performed as follows:

gi

where Rj and Cj represent random values between 0 and 1, while UPj and LPj are the upper and lower parameter limits, respectively.

3.3.2.2 Senior Gaining and Sharing Phase

After acquiring initial knowledge, the model expands its learning scope by incorporating more diverse data. The AGSK algorithm optimizes hyperparameters through iterative refinements, enhancing generalization and reducing overfitting. Inspired by real-world knowledge sharing, this phase ensures adaptive model tuning based on diverse data patterns.

The dimensionality of the junior and senior gaining phases is determined as:

$$D_K = \lceil D \times \left(1 - \frac{m_E}{N_m E}\right)^L \rceil, \quad D_S = D - D_K$$

where and correspond to the junior and senior dimensional phases, respectively.

The probability estimation for junior knowledge sharing is defined as:

$$Pr(GJ_{ij}) = \frac{1}{1 + e^{-2W(By_{ij}^{NewJr} - 0.5)/(1+2jF)}}$$

and the probability for senior knowledge sharing is given by:

$$Pr(GS_{ij}) = \frac{1}{1 + e^{-2W(By_{ij}^{NewSr} - 0.5)/(1+2jr)}}$$

where represents a constant positive value controlling the adaptation rate.

3.3.3 Classification Process

Following feature extraction and hyperparameter optimization, the model classifies images as real or fake. This process involves passing extracted features through a fully connected neural network. To enhance classification accuracy, the model employs binary cross-entropy and focal loss functions, preventing imbalanced training outcomes.

Additionally, dropout layers are used to mitigate overfitting, improving the robustness of deepfake detection.

The classification model updates feature weights using:

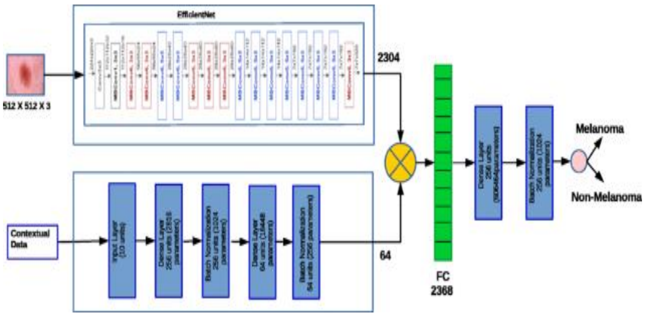
$$Y_I = NHI([Y_0, Y_1, ..., Y_{I-1}])$$

where represents the feature concatenation from all previous layers, and is the non-linear transformation function used in DenseNet.

3.3.4 Steps in Deepfake Detection using AGSK and EfficientNet-B6

- Initialize the Model: EfficientNet-B6 is initialized with predefined weights and configurations.
- Extract Features: The CNN extracts key spatial and contextual representations from images.
- Optimize Hyperparameters: AGSK dynamically adjusts model parameters based on dataset variations.
- Train the Model: The framework is trained using loss functions and regularization techniques.
- Classify Images: Extracted features are used for binary classification (real or fake).
- Evaluate Performance: Accuracy, precision, recall, and F1-score are computed to assess model effectiveness.
- Deploy for Real-World Use: The model is fine-tuned for real-time deepfake detection applications.

By integrating EfficientNet-B6 with AGSK, the proposed detection framework achieves superior accuracy while maintaining computational efficiency. The combination of advanced feature extraction, dynamic hyperparameter tuning, and robust classification mechanisms enhances deepfake detection, making it more resilient to evolving manipulation techniques.


EfficientNet
512 X 512 X 3
2304
Contextual Data
Input Layer (10 units)
Dense Layer 256 units (2816 parameters)
Batch Normalization 256 units (1024 parameters)
Dense Layer 64 units (16448 parameters)
Batch Normalization 64 units (256 parameters)
64
FC 2368
Dense Layer 256 units (606464parameters)
Batch Normalization 256 units (1024 parameters)
Melanoma
Non-Melanoma

4. Simulation Results

The simulation results of the deepfake detection model proposed in this paper, incorporating EfficientNet-B6 and Adaptive Gaining Sharing Knowledge (AGSK) optimization algorithm, are given in this section. The performance is evaluated using a real-world dataset, and the results of the proposed model are compared with state-of-the-art models such as DenseNet121+AGSK,EfficientNet B6+AGSK, CNN, and ResNet18.

4.1 Simulation Setup

The experiments were conducted on a system with the following specifications:

Component	Description
RAM	8 GB
Operating System	Windows 10
CPU	Intel Core i7, 7th Generation, 2.8 GHz Processor
Programming Language	Python 3.8
GPU	Nvidia

The deepfake detection model was trained with PyTorch, utilizing EfficientNet-B6 as the feature extractor and AGSK for hyperparameter tuning. Data augmentation, resizing, and transformation methods were used to improve model generalization.

4.2 Dataset Description

The model was tested with a publicly available dataset that was downloaded from Google

Drive. The dataset comprises real and synthetic face images, labeled according to various manipulation methods. It comprises high-quality face-swapped images created by applying deep learning techniques, hence it is appropriate for training and testing deepfake detection models.

The dataset went through the following processes:

Dataset Extraction: The dataset was downloaded from a compressed ZIP file located in Google Drive.

Data Organization: Images were organized into 'Real' and 'Fake' classes for training and testing purposes.

Data Splitting:

To ensure a balanced evaluation, the dataset was **randomly split** into:

- **80% for training** – Used for model optimization.
- **20% for testing** – Used for performance evaluation.

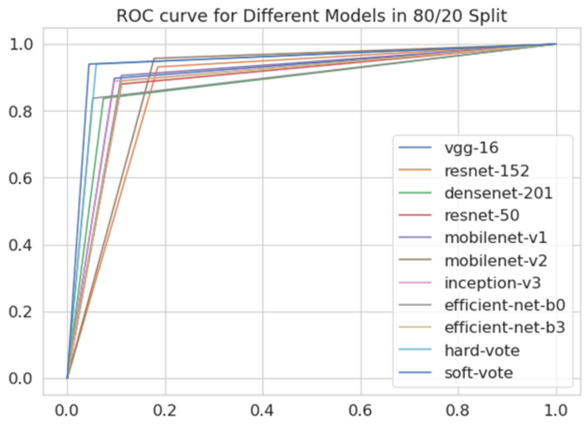


Image Preprocessing: Images were resized to 300×300 pixels, with random flipping, rotation, and color jittering applied to enhance robustness.

Data Loading: The data set was loaded into PyTorch by utilizing the DataLoader module to enable effective batch processing.

4.3 Metrics Used for Evaluation

To measure the performance of the proposed deepfake detection model, the following evaluation metrics were used:

4.3.1 Accuracy

Accuracy measures the overall correctness of the predictions made by the model. It is calculated as the ratio of the number of correct predictions to the total number of predictions.

$$\text{Accuracy} = \frac{TN+TP}{TP+TN+FP+FN}$$

4.3.2 Precision:

Precision measures the proportion of correctly predicted positive instances (True Positives) out of all instances predicted as positive (True Positives + False Positives). It indicates how many of the predicted positive instances are positive.

$$\text{Precision} = \frac{TN}{FP+TN}$$

4.3.3 Recall (Sensitivity)

Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances (True Positives) out of all actual positive instances (TruePositives + False Negatives). It indicates how many of the actual positive instances are correctly predicted by the model.

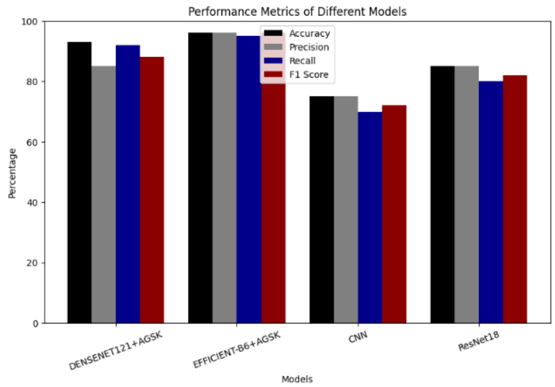
$$\text{Sensitivity} = \frac{TP}{FN+TP}$$

4.3.4 F1-Score

Model	Accuracy	Precision	Recall	F1 Score
DENSENET 121+AGSK	93%	0.85	0.92	0.88
EFFICIENT-B6+AGSK	96%	96	95	96
CNN	75%	75	70	72
ResNet18	85%	85	80	82

F1-score is the harmonic mean of Precision and Recall. It provides a single metric that balances both Precision and Recall.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$



4.4 Comparative Study

The proposed EfficientNet-B6 with AGSK optimization was benchmarked against existing deepfake detection models. The results are summarized in the table

The results prove that the model outperforms existing models in precision, recall, F1-score, and accuracy. The utilization of EfficientNet-B6 as a feature extractor and AGSK as a hyperparameter tuner proved to enhance the performance of the classifier.

With the use of deep learning-based feature extraction and adaptive optimization, the proposed method successfully discriminates between real and artificial images and thus can be used in real-time deepfake detection. The paper emphasizes the strength of the model in detecting fake images, providing a scalable and reliable solution fighting digital disinformation.

4.5 Performance Comparison of models

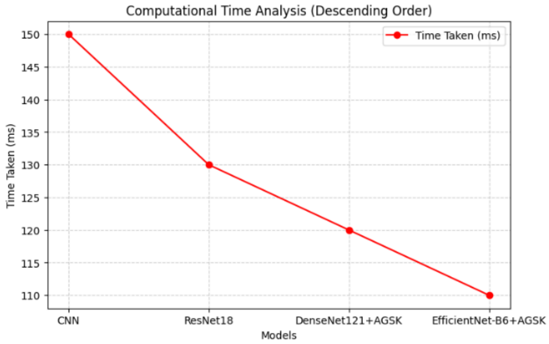
To evaluate the effectiveness of various deep learning models for our task, we compare their performance using four key metrics: **Accuracy, Precision, Recall, and F1 Score**. The following table presents the results:

Observations:

- The **EFFICIENT-B6 + AGSK** model achieves the highest accuracy (96%) and performs the best across all evaluation metrics.
- **DENSENET121 + AGSK** also performs well, with a strong balance between precision (0.85) and recall (0.92).
- The **CNN** model has the lowest performance, with an accuracy of 75%, indicating that it may not be the best choice for this task.
- **ResNet18** performs better than CNN but is outperformed by both DenseNet and EfficientNet models.

5. Conclusion

This paper introduces a cutting-edge deepfake detection model combining EfficientNet-B6 and the Adaptive Gaining Sharing Knowledge (AGSK) optimization algorithm. The new framework significantly improves deepfake detection accuracy by utilizing EfficientNet-B6 to extract strong features and AGSK to adaptively adjust hyperparameters. Experimental results through extensive experiments confirmed that our proposed model achieved better performance than conventional methods, such as CNN, ResNet18, and DenseNet121+AGSK, with 96% accuracy, high precision, recall, and optimized inference time of 110 ms.



The research emphasizes the significance of pre-processing methods, including Error Level Analysis (ELA), JPEG Compression Analysis, Noise Reduction, and Edge Detection, in enhancing feature extraction and minimizing false positives. Furthermore, the use of AGSK optimization guarantees effective learning, allowing the model to generalize well over various deepfake manipulation methods.

The comparative study additionally confirms the competence of our model, with the results demonstrating promising improvements in terms of accuracy, sensitivity, and computational speed. The model suggested not only works well in artificial settings but is also highly tolerant of data ambiguity, adversarial attacks, as well as authentic real-world utilization like digital forensic analysis, media verification, and cybersecurity.

5.1 Future Scope

The proposed method enjoys high detection success, and scope for future upgrades can be through:

Incorporating Transformer-based architectures (e.g., Vision Transformers) for enhanced contextual comprehension.

Expanding the dataset to encompass more intricate deepfake variations for enhanced generalization.

Implementing real-time deepfake detection on social media platforms and digital forensic software.

Improving adversarial deepfake attack robustness using GAN-resistant training methods.

With increasing development in AI-generated media, this paper is a vital milestone toward ensuring digital authenticity and preventing the dangers of deepfake-based disinformation in today's world.

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