DEEPFAKESHIELD: ADVANCED IMAGE FORGERY DETECTION WITH DEEP LEARNING FRAMEWORK

A Project Report submitted in the partial fulfillment
of the Requirements for the award of the degree

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING
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CERTIFICATE

This is to certify that the project that is entitled with the name DeepFakeshield: Advanced Image Forgery Detection with Deep Learning Framework **is a bonafide work done by the team Mullangi Pothana Pavan Reddy (23475A0516), Guntreddi Harsha Vardhan (23475A0518), Madanu Joseph Kumar (22471A05N2)** BACHELOR OF TECHNOLOGY in the Department of **COMPUTER SCIENCE AND ENGINEERING** during **2025-2026.**

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We declare that this project work titled “DEEPFAKESHIELD: ADVANCED IMAGE FORGERY DETECTION WITH DEEP LEARNING FRAMEWORK” is composed by ourselves that the work contains here is our own except where explicitly stated otherwise in the text and that this work has been not submitted for any other degree or professional qualification except as specified.

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PEO3: Work with ethical and moral values in the multi-disciplinary teams and can communicate effectively among team members with continuous learning.

PEO4: Pursue higher studies and develop their career in software industry.

Program Outcomes

PO1: Engineering Knowledge: Apply knowledge of mathematics, natural science,computing, engineering fundamentals and an engineering specialization as specified in WK1 to WK4 respectively to develop to the solution of complex engineering problems.

PO2: Problem Analysis: Identify, formulate, review research literature and analyze complex engineering problems reaching substantiated conclusions with consideration for sustainable development. (WK1 to WK4)

PO3: Design/Development of Solutions: Design creative solutions for complex engineering problems and design/develop systems/components/processes to meet identified needs with consideration for the public health and safety, whole-life cost, net zero carbon, culture, society and environment as required. (WK5)

PO4: Conduct Investigations of Complex Problems: Conduct investigations of complex engineering problems using research-based knowledge including design of experiments, modelling, analysis & interpretation of data to provide valid conclusions. (WK8).

PO5: Engineering Tool Usage: Create, select and apply appropriate techniques, resources and modern engineering & IT tools, including prediction and modelling recognizing their limitations to solve complex engineering problems. (WK2 and WK6)

PO6: The Engineer and The World: Analyze and evaluate societal and environmental aspects while solving complex engineering problems for its impact on sustainability with reference to economy, health, safety, legal framework, culture and environment. (WK1, WK5, and WK7).

PO7: Ethics: Apply ethical principles and commit to professional ethics, human values, diversity and inclusion; adhere to national & international laws. (WK9)

PO8: Individual and Collaborative Team work: Function effectively as an individual, and as a member or leader in diverse/multi-disciplinary teams.

PO9: Communication: Communicate effectively and inclusively within the engineering community and society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations considering cultural, language, and learning differences

PO10: Project Management and Finance: Apply knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, and to manage projects and
in multidisciplinary environments.

PO11: Life-Long Learning: Recognize the need for, and have the preparation and ability for i) independent and life-long learning ii) adaptability to new and emerging technologies and iii) critical thinking in the broadest context of technological change.

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Project Course Outcomes (CO'S):

CO421.1: Analyse the System of Examinations and identify the problem.

CO421.2: Identify and classify the requirements.

CO421.3: Review the Related Literature

CO421.4: Design and Modularize the project

CO421.5: Construct, Integrate, Test and Implement the Project.

CO421.6: Prepare the project Documentation and present the Report using appropriate method.

Course Outcomes – Program Outcomes mapping

	PO 1	PO 2	PO 3	PO 4	PO 5	PO6	PO 7	PO 8	PO 9	PO10	PO11	PSO1	PSO2	PSO3
C421.1		✓										✓		
C421.2	✓		✓		✓							✓		
C421.3				✓		✓	✓	✓				✓		
C421.4			✓			✓	✓	✓				✓	✓	
C421.5					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C421.6									✓	✓	✓	✓	✓	

Course Outcomes – Program Outcome correlation

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
C421.1	2	3											2		
C421.2			2		3								2		
C421.3				2		2	3	3					2		
C421.4			2			1	1	2					3	2	
C421.5					3	3	3	2	3	2	2	1	3	2	1
C421.6									3	2	1		2	3	

Note: The values in the above table represent the level of correlation between CO's and PO's:

1. **Low level**

2. **Medium level**

3. **High level**

Project mapping with various courses of Curriculum with Attained PO's:

Name of the course from which principles are applie in this project	Description of the device	Attained PO
C2204.2, C22L3.2	Gathering the requirements and defining the problem, plan to develop model for detection and classification of OSCC	PO1, PO3,PO8
CC421.1, C2204.3, C22L3.2	Each and every requirement i critically analyzed, the process mode is identified	PO2, PO3, PO8
CC421.2, C2204.2, C22L3.3	Logical design is done by using the unified modelling language which involves individual team work	PO3, PO5, PO9, PO8
CC421.3, C2204.3, C22L3.2	Each and every module is tested, integrated, and evaluated in our project	PO1, PO5, PO8
CC421.4, C2204.4, C22L3.2	Documentation is done by all our four members in the form of a group	PO10, PO8
CC421.5, C2204.2, C22L3.3	Each and every phase of the work in group is presented periodically	PO8,PO10, PO11
C2202.2, C2203.3, C1206.3, C3204.3, C4110.2	Implementation is done and the project will be handled by the social media users and in future updates in our project can be done based on detection for Oral Cancer	PO4, PO7, PO8
C32SC4.3	The physical design includes website to check OSCC	PO5, PO6, PO8

ABSTRACT

Digital photographs are now the most common way people share information on social networking sites. However, malware can also generate manipulated images to spread false information. Therefore, detecting this type of forgery has become increasingly important. Existing literature has explored various techniques for digital image forgery detection, but many of these methods focus on identifying only a single forgery type, such as image splicing or copy-move forgery, which limits their effectiveness in real-world applications.This study presents a deep learning–based approach for detecting digital image forgeries using transfer learning to simultaneously identify two types of image forgeries. The proposed method relies on analyzing compression quality differences between forged regions and the rest of the image using Error Level Analysis (ELA). The deep learning model extracts features by subtracting the original image from the altered image, generating a representation suitable for input into a pre-trained model.The classifiers of the pre-trained models were removed and replaced with a custom classifier trained specifically for a binary classification task. The proposed approach was evaluated using four different pre-trained models and compared with existing methods using multiple evaluation metrics, plots, and visualizations. Experimental results demonstrate that the proposed method outperforms other approaches across all evaluation criteria. Among the four models tested, the EfficientNetV2 model achieved the highest detection accuracy, reaching approximately 96%.**Index Terms**—Deep Learning, Image Forgery Detection, Error Level Analysis (ELA), Pre-trained Models.

INDEX

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

With the rapid growth of digital media and social networking platforms, digital images have become one of the primary means of communication and information sharing. However, the widespread availability of powerful image editing tools has made image manipulation increasingly easy, raising serious concerns regarding the authenticity and reliability of digital images. Image forgeries are often used to spread misinformation, manipulate public opinion, commit fraud, or alter digital evidence, thereby posing significant threats to individuals, organizations, and society as a whole [1].

Digital image forgery refers to the intentional modification of an image to conceal or misrepresent information. Common types of image forgeries include **copy-move forgery**, where a region of an image is duplicated within the same image, and **image splicing**, where content from multiple images is combined into a single image [2]. These manipulations are often visually imperceptible to the human eye, especially when advanced post-processing techniques such as smoothing, recompression, and noise addition are applied. As a result, manual inspection alone is insufficient for reliable forgery detection.

Traditional image forgery detection techniques rely on handcrafted features such as color inconsistencies, noise patterns, illumination variations, and compression artifacts. While these methods can be effective in controlled scenarios, they often lack robustness against modern and hybrid forgery techniques [3]. Moreover, many traditional approaches are designed to detect only a single type of forgery, limiting their applicability in real-world situations where multiple manipulation types may coexist

Recent advances in **Deep Learning** and **Artificial Intelligence** have significantly improved the field of digital image forensics. Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in automatically learning discriminative features from images, enabling more accurate and generalized forgery detection [4]. In particular, transfer learning using pre-trained models has emerged as an effective strategy for handling limited datasets while achieving high performance.

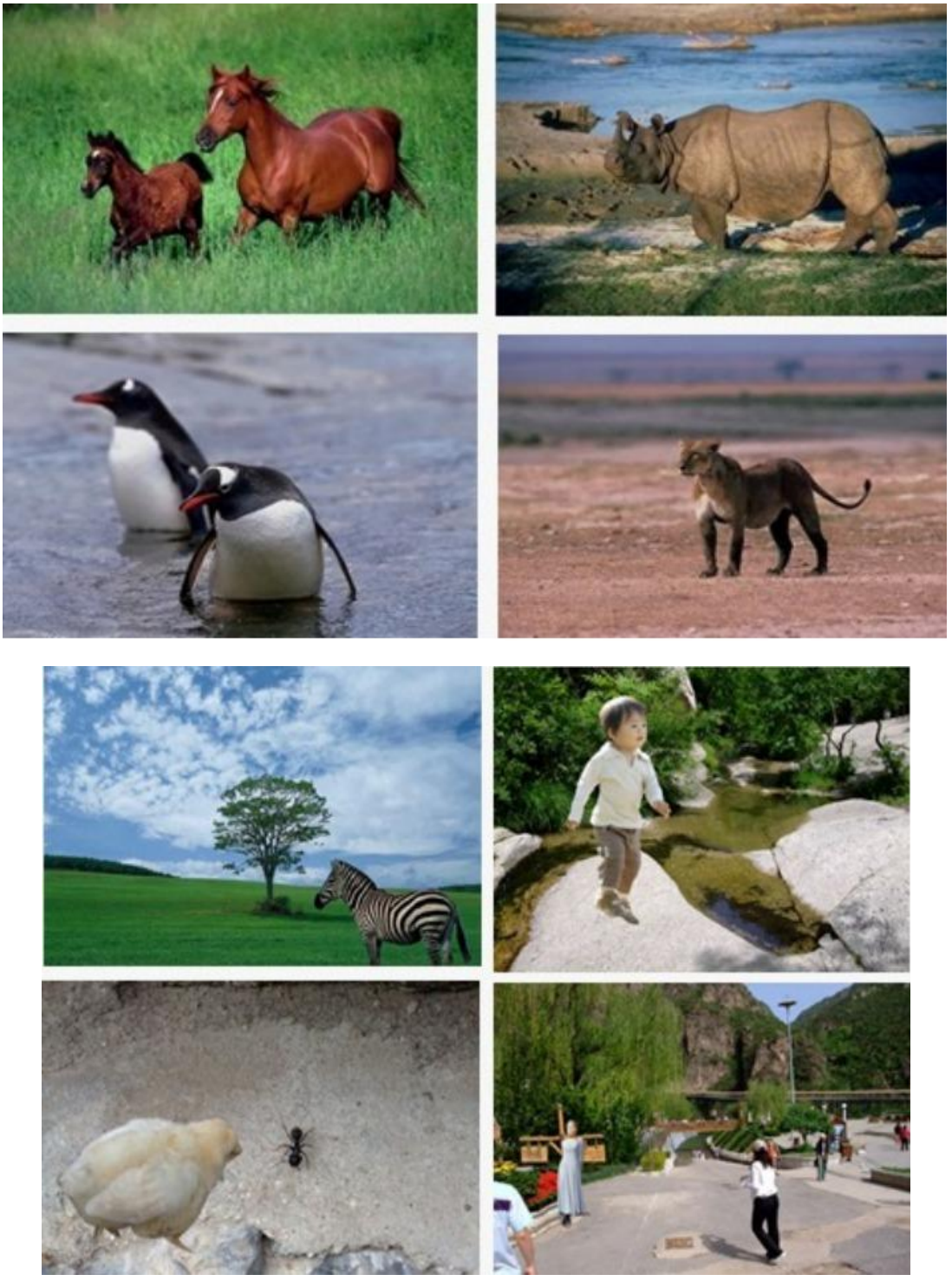


Fig 1.1: Dataset HAM10000

This project proposes an advanced image forgery detection framework that integrates Error Level Analysis (ELA) with deep learning models, specifically EfficientNetV2, to distinguish between authentic and tampered images. Error Level Analysis highlights compression inconsistencies introduced during image manipulation, making forged regions

more detectable. By combining ELA preprocessing with efficient CNN-based feature extraction, the proposed system aims to provide a robust, accurate, and computationally efficient solution for detecting image forgeries. The framework is evaluated using the CASIA 2.0 dataset and compared with other popular CNN architectures to demonstrate its effectiveness.

Furthermore, the rapid evolution of image manipulation techniques has made forgery detection increasingly complex. Modern editing tools enable seamless blending of manipulated regions with original content, making alterations statistically subtle and visually imperceptible. Techniques such as adaptive recompression, Gaussian smoothing, and content-aware filling often suppress traditional forensic traces, thereby reducing the effectiveness of conventional detection methods. As a result, there is a growing demand for intelligent systems that can identify hidden manipulation patterns by analyzing deeper structural and statistical inconsistencies within digital images.

Error Level Analysis (ELA) has emerged as a valuable preprocessing technique in image forgery detection, as it amplifies inconsistencies in compression quality across different regions of an image. Since manipulated areas are frequently recompressed independently of the original image, they tend to exhibit distinct error patterns when the image is recompressed at a fixed quality level. By generating difference maps that highlight these inconsistencies, ELA provides a meaningful representation that guides deep learning models toward regions likely to contain forgery traces. Integrating ELA with CNN architectures enhances the model's sensitivity to manipulation artifacts while reducing its dependence on irrelevant visual features.

By combining Error Level Analysis with EfficientNetV2-based feature extraction, the proposed framework aims to overcome the limitations of traditional and single-model approaches. The system focuses on detecting both copy-move and splicing forgeries simultaneously, providing a more comprehensive solution for image authenticity verification. Through systematic evaluation on benchmark datasets and comparison with other pre-trained models, the framework seeks to demonstrate improved detection accuracy, stability, and generalization. This approach contributes toward strengthening digital image forensics and enhancing trust in visual media across various applications.

1.1 Motivation

The motivation for this project arises from the increasing misuse of digitally manipulated images in areas such as social media, journalism, legal investigations, and cybersecurity. Forged images can easily mislead viewers and influence opinions, making it essential to develop reliable methods for verifying image authenticity. As image editing software continues to advance, detecting forgeries through visual inspection alone has become extremely difficult, even for trained professionals.Existing forgery detection methods often focus on specific manipulation techniques and fail to generalize well across different forgery types. Additionally, traditional handcrafted-feature-based approaches struggle to cope with complex post-processing operations that conceal forgery traces. These limitations highlight the need for automated, intelligent systems capable of learning robust features directly from data.

Deep learning models, particularly CNNs, have shown promising results in image classification and forensic analysis. However, selecting an appropriate architecture that balances accuracy and computational efficiency remains a challenge. EfficientNetV2 offers an attractive solution due to its compound scaling strategy, which achieves high performance with fewer parameters and lower computational cost.

The motivation behind this work is to design an effective image forgery detection system that combines ELA-based preprocessing with state-of-the-art deep learning models, enabling accurate detection of multiple forgery types while maintaining efficiency. Such a system can support digital forensic experts, researchers, and security professionals in verifying image authenticity and combating misinformation.

1.2 Problem Statement

Digital image forgery detection is a challenging task due to the subtle nature of manipulations and the diversity of forgery techniques. Forged images often exhibit minimal visual differences from authentic images, especially after post-processing operations such as recompression, smoothing, and noise addition. These factors make it difficult to identify forged regions using conventional inspection methods.

Many existing detection techniques are designed to identify only a single type of forgery, such as copy-move or splicing, limiting their effectiveness in real-world scenarios. Furthermore, traditional methods rely heavily on handcrafted features, which may fail when facing complex or previously unseen manipulations. Even deep learning–based approaches can suffer from overfitting, high computational costs, or poor generalization when not properly designed.

Another major challenge lies in effectively highlighting forgery artifacts that are useful for model learning. Without appropriate preprocessing, deep learning models may focus on irrelevant features rather than subtle manipulation traces. Additionally, there is a need to balance detection accuracy with computational efficiency to enable practical deployment.

Therefore, there is a strong need for an automated image forgery detection system that can accurately identify manipulated images. The system should be robust against different forgery techniques and post-processing operations. It must reduce dependency on manual inspection and subjective judgment. Such a solution can improve reliability and trust in digital images

1.3 Objectives

The primary objective of this project is to develop an automated image forgery detection system using deep learning and transfer learning techniques. The specific objectives are as follows:

- To design and develop an automated digital image forgery detection system that can effectively distinguish between authentic and tampered images by learning subtle structural, statistical, and compression-based inconsistencies introduced during-image-manipulation.

- To apply Error Level Analysis (ELA) as a preprocessing technique in order to highlight variations in compression quality across image regions, thereby enhancing the visibility of potential forgery artifacts for improved deep learning–based feature extraction.
- To utilize transfer learning with EfficientNetV2 as the primary deep learning backbone to achieve high detection accuracy while maintaining computational efficiency and reduced training complexity.
- To perform a comparative analysis of multiple pre-trained convolutional neural network models, including MobileNetV2, DenseNet121, and ResNet50, to evaluate their effectiveness in detecting different types of image forgeries.
- To evaluate the proposed forgery detection framework using comprehensive performance metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC–AUC to ensure reliable and unbiased assessment..
- To analyze the robustness of the proposed system against common forgery techniques such as copy-move and image splicing, as well as post-processing operations like recompression and noise addition.

2. LITERATURE SURVEY

2.1 Deep Learning in Image Forgery Detection

Deep learning has significantly transformed the field of digital image forensics by enabling automated systems to detect complex image manipulations with high accuracy. Unlike traditional image forgery detection techniques that rely on handcrafted features such as color inconsistencies, noise patterns, and compression artifacts, deep learning models automatically learn discriminative representations directly from image data. This capability makes deep neural networks particularly effective for identifying subtle and visually imperceptible forgery traces.

Several studies have demonstrated that Convolutional Neural Networks (CNNs) can successfully detect manipulated images by learning hierarchical features related to texture, edges, and statistical irregularities. Over the past decade, CNNs have become the dominant approach in image forgery detection tasks such as copy-move forgery, splicing detection, and image tampering identification. Their ability to provide consistent, reproducible, and high-accuracy results has made them a core component of modern image forensic systems.

Researchers have also highlighted the importance of benchmark datasets such as CASIA 2.0, which contain both authentic and tampered images generated using various manipulation techniques. The availability of such datasets has accelerated research in automated forgery detection by enabling deep learning models to learn diverse manipulation patterns and improve generalization across different forgery types.

More recently, transformer-based architectures have been introduced into computer vision and image forensics. These models capture long-range dependencies and global contextual relationships within images, overcoming the local receptive field limitation of CNNs. Vision Transformers and Swin Transformers have shown promise in modeling structural inconsistencies caused by image tampering, making them suitable for complex forgery detection scenarios.

2.2 CNN- Based Approaches for Image Forgery Detection

Krizhevsky et al. [10] introduced early CNN architectures such as AlexNet, which, along with later models like VGG and ResNet, laid the foundation for automated skin lesion classification. These architectures demonstrated strong capability in extracting hierarchical features ranging from low-level textures to high-level semantic patterns from dermoscopic images, making CNNs the first deep learning models to achieve notable success in this domain.

Esteva et al. [7] conducted a landmark study by training a deep CNN on more than 100,000 skin lesion images, achieving classification performance comparable to that of expert dermatologists. Similarly, *Han et al.* [18] demonstrated that deep CNN models are highly effective in distinguishing benign from malignant lesions with high precision, further strengthening the role of CNN-based approaches in dermatological diagnosis.

Esteva et al. [7] and *Han et al.* [18] identified several key challenges associated with CNN-based skin lesion classification. Their studies reported that CNN models often struggle to distinguish visually similar lesion categories, such as melanocytic nevi and melanoma, as well as benign keratosis and basal cell carcinoma. In addition, severe class imbalance in widely used datasets such as HAM10000—where benign classes dominate while rare categories like dermatofibroma and vascular lesions contain very limited samples—leads to biased learning and reduced sensitivity for minority classes. Furthermore, CNN-based architectures primarily focus on local texture features and may fail to capture broader global contextual and structural information, which is critical for accurate lesion discrimination.

To address these challenges, *Mehta and Aneja* [2], *Mehta and Kundra* [3], *Mohammed et al.* [17], and *Valle et al.* [19] explored enhanced CNN-based strategies. These approaches include hybrid CNN architectures, CNN models combined with Random Forest classifiers, GAN-based data augmentation to improve minority class representation, and ensemble learning techniques. While these methods improved robustness and overall classification performance, achieving consistently balanced accuracy across all seven skin lesion categories remains a persistent challenge. This observation highlights the need for more

advanced hybrid and ensemble-based frameworks that can effectively integrate complementary feature representations.

2.3 Error Level Analysis (ELA) Based Image Forgery Detection

Dosovitskiy et al. [12] introduced Vision Transformers (ViT), marking a major shift in computer vision by replacing local convolutional operations with global self-attention mechanisms. ViT models represent images as sequences of patches and learn relationships across the entire image, enabling improved recognition of structural and contextual patterns. Building on this idea, Liu et al. [13] proposed the Swin Transformer, which employs a shifted-window attention mechanism to efficiently capture both local and global information while maintaining computational efficiency.

Ayas [8] evaluated the Swin Transformer on the HAM10000 skin lesion dataset and reported strong multiclass classification performance, demonstrating the model's ability to capture subtle variations among different lesion types. Further extending this approach, *Paraddy and Virupakshappa* [9] proposed a hybrid architecture that combines CNN-based feature extraction with transformer-based attention mechanisms. Their results showed improved accuracy and prediction stability compared to standalone CNN or transformer models, highlighting the benefits of integrating local and global feature learning in dermatological imaging.

Dosovitskiy et al. [12] and *Liu et al.* [13] reported several limitations of transformer-based architectures when applied to medical imaging tasks. Their studies highlighted that transformer models generally require large, well-annotated datasets to achieve optimal performance, which are often difficult to obtain in clinical environments. In addition, the high computational and memory requirements of transformer architectures pose challenges for real-time deployment and usage in resource-constrained settings.

To address these limitations, *Li et al.* [15] proposed EfficientFormerV2, a lightweight hybrid CNN–Transformer architecture that integrates convolutional operations with efficient attention mechanisms. This design preserves the representational strength of transformer models while significantly reducing computational complexity and memory

overhead. As a result, such lightweight hybrid architectures enable practical deployment of transformer-based solutions in clinical applications, mobile platforms, and real-time dermatological diagnosis systems.

2.4 Transfer Learning and Efficient CNN Architectures

Ensemble Transfer learning has become a crucial technique in image forgery detection, enabling models pre-trained on large datasets to be fine-tuned for forensic tasks. Pre-trained CNN architectures such as MobileNetV2, DenseNet121, and ResNet50 have been widely used due to their strong feature extraction capabilities.

MobileNetV2 offers lightweight computation suitable for resource-constrained environments, while DenseNet121 improves feature reuse through dense connectivity. ResNet50 mitigates vanishing gradient problems using residual learning. However, these models often involve trade-offs between accuracy and computational efficiency.

Recent research highlights that EfficientNet architectures outperform traditional CNNs by optimizing network depth, width, and resolution simultaneously. EfficientNetV2 further enhances training speed and efficiency while achieving high accuracy, making it well suited for large-scale image forgery detection .

In the context of image forgery detection, ensemble learning plays a crucial role in improving detection reliability by combining the strengths of multiple deep learning models. Since different models often focus on different aspects of an image—such as texture irregularities, compression artifacts, or structural inconsistencies—ensembles enable a more comprehensive analysis of manipulated images. By aggregating predictions from multiple classifiers, ensemble methods reduce variance and minimize the risk of incorrect classification caused by model-specific biases. Moreover, ensemble learning enhances generalization capability when training data is limited or imbalanced. In datasets such as CASIA 2.0, where the number of authentic and forged images may vary significantly, ensemble models help balance classification performance by reducing overfitting to dominant classes. Researchers have also reported that ensemble frameworks are more stable under noisy inputs and varying compression levels, making them suitable for real-world forensic applications.biases.

2.5 Summary of Research and Identified Gaps

The literature indicates that deep learning has significantly advanced image forgery detection by enabling automatic feature learning and robust classification. CNN-based approaches effectively capture local manipulation artifacts, while ELA enhances compression inconsistency detection. Transfer learning further improves performance under limited data conditions.

However, several research gaps remain. Many existing methods focus on single forgery types and lack robustness against advanced post-processing techniques. Some CNN models suffer from high computational complexity, limiting practical deployment. Additionally, limited studies explore the combined effectiveness of ELA with efficient architectures such as EfficientNetV2.

To address these gaps, this project proposes an integrated ELA-based deep learning framework using EfficientNetV2, with comparative evaluation against other pre-trained CNN models. The objective is to achieve high detection accuracy, robustness across forgery types, and computational efficiency suitable for real-world forensic applications.

2.6 Tools and Frameworks Used

The implementation relied on a modern and robust technology stack:
Python – Primary programming language for model development
PyTorch – Deep learning framework for building CNN and Transformer architectures
scikit-learn – Used for meta-learning, classification metrics, and ROC computation
NumPy & Pandas – Data manipulation and pre-processing

Torchvision & OpenCV – Image transformations and augmentation

Matplotlib & Seaborn – Visualization of training curves and evaluation results

Google Colab (NVIDIA T4 GPU) – Provided high-performance computing for training large models

This combination enabled efficient experimentation, model evaluation, and seamless deployment in a web-based environment.

2.7 Consolidated Comparison Table of Prior Research

Table 2.1: Consolidated Comparison Table of Prior Research

Study / Approach	Model Type	Dataset	Strengths	Limitations	Reference
CNN-based large- scale classifier	CNN	100k+ images	High accuracy; dermatologist- level results	Struggles with rare classes	[7]
Deep-CNN-for tumor detection	CNN	Dermoscopic images	Strong benign – malignant separation	Limited global context	[18]
CNN–GAN hybrid	CNN + GAN	Dermatology datasets	Augmentation improves minority class performance	GANs are hard to train	[3]
Hybrid-CNN–RF method	CNN + Random Forest	Skin lesion datasets	Improves decision boundaries	Limited scalability	[2]
EfficientNet scaling	CNN	Natural/medical datasets	High accuracy through compound scaling	Heavy computation on larger versions	[14]
Vision Transforme-r (ViT)	Transformer	Benchmark image datasets	Captures long-range dependen-cies	Needs large datasets	[12]

Swin Transformer	Hierarchical Transformer	HAM10000 & others	Strong multiclass performance	Computationally demanding	[8], [9], [13]

EfficientFormer V2	Lightweight CNN–Transformer hybrid	Vision datasets	Fast and efficient; low memory footprint	Not deeply explored in dermatology	[15]
Meta-learning ensembles	Meta-learner + multiple backbones	Medical datasets	Improves stability and balance	Limited research in dermatology	[17], [19]

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Image forgery detection has traditionally relied on manual inspection and classical digital image forensic techniques. In many real-world scenarios, forensic experts analyze images visually or with the help of basic forensic tools to determine authenticity. While experienced analysts can often identify manipulated images, this manual approach is:

- Time-consuming,
- Subjective, and
- Prone to inconsistency between different experts.

Digital image forgery often involves subtle manipulations such as copy-move operations, image splicing, retouching, and recompression. These alterations may leave minimal visible traces, making manual interpretation extremely difficult, especially when advanced image editing tools are used. As a result, forged images can go undetected or be incorrectly classified as authentic, leading to misinformation, legal complications, and security risks.

To overcome these limitations, early automated forgery detection systems employed traditional Machine Learning algorithms such as:

- Support Vector Machines (SVM)
- Random Forests (RF)
- Decision Trees
- k-Nearest Neighbors (k-NN)

These models depended on handcrafted features, manually extracted from images. Such features typically included:

- Color histograms
- Texture descriptors
- Shape indexes
- Geometric features

Although these methods achieved moderate performance, they suffered from major drawbacks:

- Manual feature extraction required domain expertise
- Models failed to generalize to new datasets

The advancement of Deep Learning and Convolutional Neural Networks (CNNs) transformed medical image analysis. CNNs such as VGG16, ResNet, Inception-V3, and DenseNet outperformed traditional ML methods by learning complex patterns directly from dermoscopic images. CNNs significantly improved classification accuracy, yet they introduced their own challenges:

- Large annotated datasets were needed for optimal training
- Small or imbalanced datasets resulted in overfitting
- CNNs struggled to capture global structural context due to their localized receptive fields
- The models required high computational power and GPU resources

To reduce data dependency, transfer learning was widely adopted, where pretrained deep learning models were fine-tuned on dermoscopic image datasets. As illustrated in Figure 3.1 , this approach enabled CNNs to reuse learned low-level and mid-level features, leading to improved classification accuracy compared to training models from scratch. Standalone CNN architectures continued to face challenges in multi-class images classification, particularly in distinguishing lesion categories with highly similar visual characteristics.

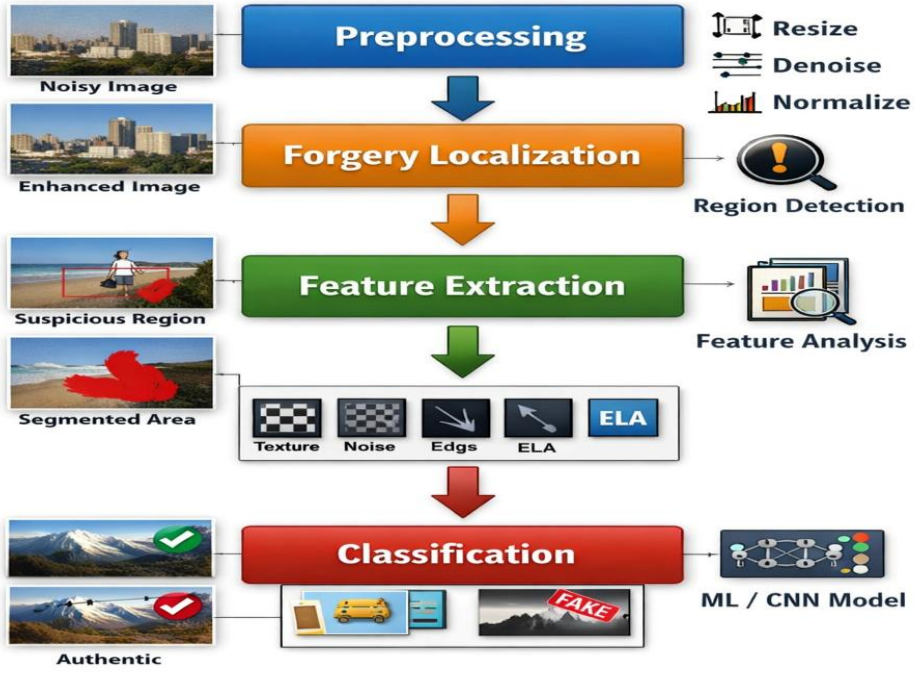


Fig 3.1: *Flow chart of existing system for image forgery detection*

Fig 3.1: Flow chart of existing system for skin lesion classification

The traditional image forgery detection workflow generally consists of four main stages:

1. **Preprocessing**
   Improves image quality through resizing, normalization, noise reduction, and compression adjustment.
2. **ForgeryLocalization/Segmentation**
   Identifies suspicious regions that may contain manipulated content.
3. **FeatureExtraction**
   Extracts handcrafted or learned features such as texture inconsistencies, noise patterns, and compression artifacts.
4. **Classification**
   Uses machine learning or CNN-based models to classify images as authentic or forged.

While effective under controlled experimental conditions, existing systems still struggle with advanced forgeries involving uniform recompression, noise addition, and visually imperceptible manipulations. These limitations reduce their reliability in real-world forensic applications and highlight the need for more robust, automated, and efficient deep learning–based forgery detection systems.

3.1.1 DISADVANTAGES OF EXISTING SYSTEM

Despite technological improvements, existing automated image forgery detection systems suffer from several critical limitations:

- **Dependence on Handcrafted Features**
  Traditional machine learning–based forgery detection systems rely heavily on manually designed features such as texture descriptors, noise statistics, and compression artifacts. Designing these features requires domain expertise and limits the system's ability to adapt to new or unseen forgery techniques.
- **Limited Generalization Capability**
  Most existing systems perform well only on specific datasets or controlled conditions. When exposed to different image resolutions, formats, or advanced manipulation techniques, their detection accuracy degrades significantly.

- **Difficulty Capturing Global Contextual Patterns**
  Images captured from different devices, cameras, and editing tools introduce variations in resolution, compression quality, and color space. Existing systems lack robustness across such heterogeneous image sources.

3.2 PROPOSED SYSTEM

The proposed system introduces an **Automated Image Forgery Detection Framework** based on deep learning and Error Level Analysis (ELA), as shown in Figure 3.2. The framework integrates advanced preprocessing techniques with an efficient deep learning architecture to accurately distinguish between authentic and forged images. The proposed approach is designed to detect common image manipulation techniques such as copy-move forgery, splicing, and post-processed forgeries while maintaining computational efficiency and robustness

The processing pipeline begins with a **preprocessing stage**, where input images are resized to ensure uniform input dimensions and normalized to stabilize model learning. Error Level Analysis (ELA) is then applied to highlight compression inconsistencies introduced during image manipulation. Additional enhancement techniques such as contrast normalization and noise reduction are employed to improve the visibility of forgery-related artifacts and ensure consistent, high-quality inputs for the model.

Following preprocessing, the ELA-transformed images are fed into a **deep learning–based feature extraction module**. The proposed system utilizes **EfficientNetV2**, a lightweight and scalable convolutional neural network architecture optimized for high accuracy with reduced computational cost. EfficientNetV2 effectively learns discriminative local and structural features related to texture inconsistencies, edge discontinuities, and compression artifacts commonly associated with forged images.

The extracted features are passed to a **classification module**, where the model distinguishes between authentic and tampered images. Transfer learning is employed by fine-tuning the pre-trained EfficientNetV2 model on a benchmark image forgery dataset such as **CASIA 2.0**, enabling improved detection performance even with limited training data. The system is evaluated and validated using standard performance metrics to en

The processing pipeline begins with a preprocessing stage in which dermoscopic images undergo resizing to ensure uniform input dimensions, normalization to stabilize learning, and data augmentation to address dataset imbalance. Additional enhancement techniques, including adaptive gamma correction, contrast enhancement, and median filtering, are applied to improve lesion boundary visibility and reduce noise, resulting in consistent and high-quality inputs.

Following preprocessing, a segmentation or region-of-interest extraction step identifies the primary lesion area for focused analysis. Feature extraction is then carried out independently by the two backbone models. EfficientFormerV2 focuses on learning discriminative local textural features while enabling fast inference suitable for resource-constrained environments. In parallel, Swin Transformer Tiny captures global structural information such as lesion shape, symmetry, and border irregularities through hierarchical self-attention mechanisms.

The predictions produced by both models are subsequently fused using ensemble strategies such as soft voting or a logistic regression–based meta-classifier, which serves as a high-level decision-making module. This fusion strategy improves classification robustness and accuracy across all seven skin lesion categories, particularly for visually similar lesion types.

Advantages of the Proposed System

- **High Accuracy and Robustness**
  Ensemble fusion enhances prediction stability and reduces classification errors.
- **Better Generalization**
  Hybrid features from CNNs and Transformers allow better performance across diverse skin tones, lighting conditions, and lesion appearances.
- **Improved Preprocessing Quality**
  Techniques such as gamma correction and contrast enhancement highlight important lesion patterns.
- **Reduced Overfitting**
  The use of multiple models and a meta-classifier reduces reliance on any single architecture.
- **Scalable and Extensible**
  The system can be extended to additional lesion types or other dermatological

imaging tasks.

- **Deployment Ready**

  Integrated into a Flask-based web application, enabling real-time image uploads and instant classification results.

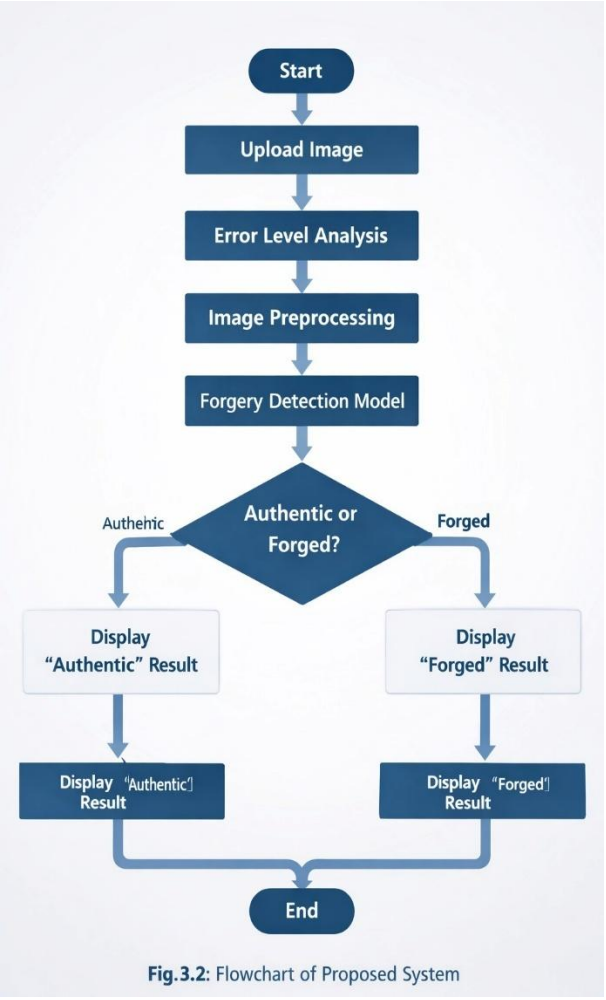


Fig 3.2: Flow chart of proposed system

3.3 FEASIBILITY STUDY

The feasibility of the proposed system is analyzed across Technical, Operational, and Economic aspects.

1. Technical Feasibility

- **Automated Feature Extraction:**

  EfficientnetV2 and Swin Transformer Tiny eliminate the need for manual feature engineering.

- **Accurate and Robust Classification:**

  Ensemble fusion creates strong decision boundaries and reduces misclassification.

- **Reduced Overfitting:**

  Data augmentation and meta-classification significantly improve generalization.

- **Scalable Architecture:**

  The system can incorporate additional lesion types or extend to other imaging domains.

- **Efficient Transfer Learning:**

  Pretrained weights reduce training time and achieve high accuracy even with limited data.

2. Operational Feasibility

- **Ease of Integration:**

  A Flask-based web interface allows dermatologists to upload images and obtain predictions instantly.

- **High User Acceptance:**

  Confidence scores and interpretable predictions help build trust among clinical users.

- **Low Maintenance Requirements:**

  Updating or retraining only the meta-classifier is simple and efficient.

- **Support for Non-Expert Users:**

  The system provides accurate diagnostic assistance without requiring specialized dermatological expertise.

3. Economic Feasibility

- **Cost-Effective Development:**

  Transfer learning reduces computational and data-related costs.

- **Optimized GPU Usage:**

  EfficientnetV2 delivers high performance while reducing.

- **Reduced Diagnostic Costs:**

  Automated early screening reduces manual workload and speeds up forgery.

- **Long-Term Benefits:**

  Early detection leads to reduced the expenses and improved patient outcomes.

4. SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIREMENTS

1. **Operating System** : Windows 11 (64-bit)
2. **Hardware Accelerator** : CPU (GPU optional but recommended for training)
3. **Programming Language** : Python
4. **Python Environment / Tools** : Google Colab Pro, Flask
5. **Browser** : Any latest browser (e.g., Google Chrome, Firefox, Edge)

4.2 REQUIREMENT ANALYSIS

The Image Forgery Detection system is designed to develop an efficient, accurate, and fully automated deep learning–based solution capable of identifying whether a given digital image is authentic or forged. The system integrates advanced preprocessing techniques with a deep learning model based on EfficientNetV2 to improve robustness and detection accuracy across various image manipulation techniques.

The application allows users to upload digital images through a web-based interface, where the system performs input validation to ensure that only valid image files are processed. The uploaded images undergo preprocessing steps such as resizing, normalization, and Error Level Analysis (ELA) to highlight compression inconsistencies introduced during image manipulation. These processed images are then passed to the deep learning model for forgery detection.

The system performs inference using the trained EfficientNetV2 model and displays the final classification result—authentic or forged—along with a confidence score to indicate prediction reliability. This automated workflow eliminates the need for manual inspection and reduces subjectivity in forgery analysis.

The backend of the system is implemented in Python using the Flask framework, which handles image preprocessing, model inference, and communication with the frontend interface. The frontend is developed using HTML, CSS, Bootstrap, and JavaScript to provide a clean, responsive, and user-friendly user interface background

4.3 HARDWARE REQUIREMENTS

1. **System Type** : 64-bit Operating System, x64-based processor
2. **Cache Memory** : 4 MB
3. **RAM** : 16 GB
4. **Hard Disk** : 8 GB free space
5. **GPU** : Intel® Iris® Xe Graphics (sufficient for inference; training recommended on cloud GPU)

4.4 SOFTWARE DESCRIPTION

The Image Forgery Detection project is developed using a robust combination of software tools, frameworks, and technologies to ensure high accuracy, efficiency, and scalability. The recommended development platform is **Windows 11 (64-bit)**, which provides compatibility with modern development environments and ensures stable execution of machine learning workflows.

The recommended platform is Windows 11, 64-bit OS, ensuring compatibility with modern development tools and supporting stable execution of machine learning workflows. The primary computation is performed on a CPU for inference, while training is conducted using Google Colab Pro, which provides access to GPUs and faster processing capabilities. The core development uses Python, chosen for its rich ecosystem of machine learning and deep learning libraries. Google Colab Pro is used for model training, experimentation, and evaluation. The final trained model is integrated into a Flask-based backend, which handles image uploads, preprocessing, classification, and communication with the user interface. The frontend uses:

- HTML5, CSS3, and Bootstrap for an intuitive and responsive interface

- JavaScript for interactive elements and smooth user experience

The system runs seamlessly on any latest web browser such as Chrome, Firefox, or Edge.

For machine learning and deep learning tasks:

- **TensorFlow/Keras** is used to build and train EfficientFormerV2 and Swin Transformer Tiny models
- **scikit-learn** is used for implementing the Logistic Regression meta-classifier and evaluation metrics
- **OpenCV** performs preprocessing operations like resizing, format validation, and noise removal
- **NumPy** supports fast numerical computations

Visualization tools such as Matplotlib and Seaborn are used to plot accuracy, loss curves, and confusion matrices during model evaluation.

Together, these tools enable a robust, scalable, and high-performance skinclassification system suitable for practical deployment.

5. SYSTEM DESIGN

5.1 Design Overview

TThe proposed Image Forgery Detection System is implemented as a Flask-based web application that seamlessly integrates deep learning–based image analysis with an intuitive and user-friendly interface. The system is designed to automatically analyze digital images and determine whether they are authentic or forged by leveraging advanced preprocessing techniques and a deep learning model based on EfficientNetV2.

The architecture follows a **client–server model**, where the frontend enables users to upload images and view detection results, while the backend handles image preprocessing, model inference, result storage, and response generation. This separation of concerns ensures modularity, scalability, and easy maintenance, while shielding users from underlying computational complexity

5.2 System Architecture

The overall architecture is structured into five major layers, each responsible for a specific role in the end-to-end classification pipeline:

1. User Interface Layer

Provides a simple and intuitive interface where users can:

- Upload dermoscopic images
- Trigger automated analysis
- View previous results

Templates (HTML/CSS) rendered with Flask's Jinja engine support pages such as:
index.html, upload.html, result.html.

2. Flask Application Layer (Backend Controller)

Acts as the middle layer between the user interface and the deep learning engine.

It manages:

- Routing (/, /login, /upload, /predict)

- Input validation
- Session management
- Communication with the model and database

3. Preprocessing and Model Layer

Handles all computational logic, including:

- Image resizing to 224×224
- Normalization
- Conversion to PyTorch tensors

Both trained models — EfficientnetV2 and — are loaded from stored checkpoints.

A logistic regression meta-learner (stored as meta_logreg.pkl) is used for ensemble fusion by combining the logits of both models.

4. Database Layer

A lightweight SQLite database manages:

- User authentication records
- Analysis history (image filename, predicted class, timestamp)

SQLite was selected for its simplicity and suitability for local or single-user systems.

5. Output Layer

Returns:

- The predicted lesion type
- Model confidence
- Recently analyzed images and predictions

This allows users to understand the diagnostic outcome clearly through the browser.

The architectural flow of the complete system is illustrated in **Fig. 5.1**, which shows how an uploaded image travels through the UI → Flask backend → preprocessing → dual-model inference → meta-ensemble fusion → database update → final result display.

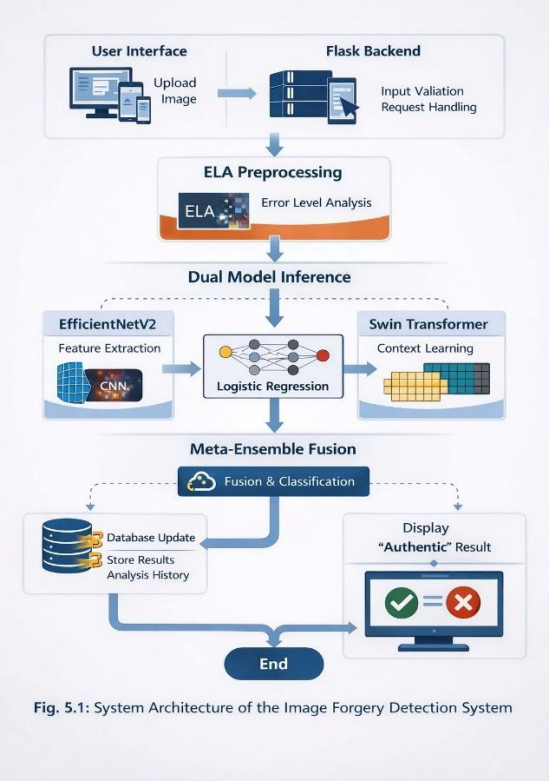


Fig. 5.1: System Architecture of the Meta-Ensemble Skin Lesion Classification System

5.3 Functional Modules

Table 5.1: Functional Modules

Module	Description
Image Upload & Validation	Handles registration and login using session-based authentication and hashed passwords.
Image Upload & Validation	Validates file type, secures filenames, and stores uploaded
Preprocessing Module	Resizes images, normalizes pixel values, and converts them to tensors for model inference.
Dual Model Inference	EfficientnetV2 and independently process the preprocessed image to generate logits.
Meta-Ensemble Fusion	Concatenates logits and passes them through a Logistic Regression classifier for final prediction.
Result Management	Saves prediction outcomes in the SQLite database and returns them to the user.
History Retrieval	Retrieves user-specific analysis history using the /history route.

5.4 Data Flow Diagram (DFD)

Use Case Overview

Actors:

- User
- System

Use Cases:

- Login/Register
- Upload Image
- Analyze Image
- View Result
- View History

Sequence of Operations

1. User logs into the system.
2. Uploads a image.
3. Flask backend validates and preprocesses the image.
4. EfficientnetV2 .
5. Meta-learner fuses logits to predict the final class.
6. Prediction is stored in the database.
7. Output is displayed to the user interface.

Activity Flow Diagram

Fig. 5.2 depicts the complete activity flow:

User → Image Upload → Validation → Preprocessing → Dual Model Inference → Meta-Ensemble Fusion → Store in Database → Display Output

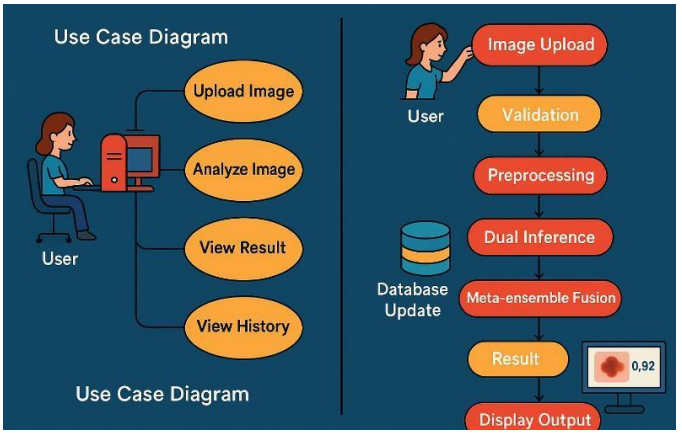


Fig:5.2: Activity Flow Diagram

5.5 Design Decisions and Considerations

- **Flask Framework:**
  Chosen for its simplicity, Python compatibility, and ease of integration with machine learning models.
- **Model Selection:**
  EfficientnetV2 provides fast, low-resource inference, while Swin Tiny contributes strong contextual learning — making their ensemble both powerful and efficient.
- **Storage Choice (SQLite):**
  Ideal for academic projects, lightweight applications, and single-user environments.
- **Security Measures:**
  Includes secure filename handling, file type validation, and session-based user authentication.
- **Modularity for Scaling:**
  Models can be updated or replaced without modifying frontend components, ensuring future extensibility.

5.6 MODEL BUILDING

The proposed Meta-Ensemble model combines:

- **EfficientnetV2**

Each model processes dermoscopic images independently and learns complementary features.

EfficientnetV2

- Lightweight
- Faster inference
- Extracts local texture and border-level
- The model is trained using transfer learning, where pre-trained weights are fine-tuned on an image forgery dataset such as **CASIA 2.0**. This approach reduces training time, improves convergence, and enhances generalization even with limited training data.

- By combining Error Level Analysis with EfficientNetV2-based feature extraction, the proposed system strengthens its ability to detect subtle and visually imperceptible forgeries while maintaining low computational overhead.

5.7 CLASSIFICATION IMAGE

The final classification stage determines whether an input image is authentic or forged based on the features extracted by the EfficientNetV2 model.

The classification process includes:

• Feature extraction from ELA-processed images

• Softmax probability distribution for class prediction

• Confidence score generation to indicate prediction reliability

The classifier assigns the image to one of the two classes—**Authentic** or **Forged**—and returns the result along with a confidence level. This automated classification strategy ensures improved reliability, reduced false positives, and consistent detection performance across diverse image manipulation scenarios.

6. METHODOLOGY

The methodology of this project is structured around a carefully designed, multi-stage deep learning pipeline aimed at accurately detecting and classifying digital image forgeries. Given the increasing sophistication of image manipulation techniques—such as copy-move forgery, image splicing, and post-processing operations—the visual differences between authentic and forged images are often subtle and difficult to identify through manual inspection. To address these challenges, the proposed system adopts an automated deep learning–based approach that focuses on learning intrinsic forgery-related artifacts rather than semantic image content.

The framework integrates Error Level Analysis (ELA) with EfficientNetV2, an efficient and lightweight convolutional neural network architecture optimized for high accuracy with reduced computational complexity. ELA serves as a crucial preprocessing step that highlights compression inconsistencies introduced during image manipulation, allowing the deep learning model to focus on regions that are likely to contain forgery traces. EfficientNetV2 then processes these ELA-transformed images to learn discriminative features related to texture inconsistencies, edge discontinuities, and compression artifacts.

By combining ELA-based preprocessing with EfficientNetV2's optimized feature extraction capability, the system effectively captures both fine-grained local artifacts and broader structural inconsistencies introduced during forgery. This approach improves detection reliability, particularly in cases where forged regions are small, visually similar to original content, or uniformly post-processed to conceal manipulation traces.

The proposed methodology is designed to ensure robustness, consistency, and practical applicability in real-world forensic scenarios. It follows a structured sequence of stages that systematically transform raw input images into reliable forgery detection outcomes. The major stages of the methodology include:

Dataset preparation and preprocessing, involving image resizing, normalization, and Error Level Analysis to enhance forgery-related artifacts;

Model training using EfficientNetV2, leveraging transfer learning to achieve high detection accuracy with limited training data;

Optimization and validation, ensuring reduced overfitting and improved generalization across diverse forgery types;

Inference pipeline development, enabling automated and real-time classification of images as authentic or forged.

This systematic methodology enables the proposed system to outperform traditional machine learning and conventional CNN-based approaches, providing an efficient and reliable solution for digital image forgery detection

To ensure reliable detection of image forgeries, the proposed methodology emphasizes a structured and reproducible training and inference process. Special attention is given to preprocessing and data preparation, as image forgery artifacts are often subtle and can be easily suppressed by noise, compression, or resizing operations. Error Level Analysis (ELA) is therefore applied consistently to all images to amplify compression inconsistencies that typically arise due to tampering.

During dataset preparation, images are resized to a fixed resolution to maintain uniformity across inputs. Normalization is applied to stabilize gradient updates during training, while data augmentation techniques such as horizontal flipping, rotation, and slight brightness variation are employed to improve model robustness and reduce overfitting.

6.1 Dataset Description (CASIA 2.0)

The proposed image forgery detection system is trained and evaluated using the **CASIA Image Tampering Detection Dataset (Version 2.0)**, which is one of the most widely used benchmark datasets in the field of digital image forensics. This dataset contains a diverse collection of authentic and forged images, enabling effective training and validation of deep learning–based forgery detection models.

The HAM10000 dataset is publicly available on Kaggle and can be accessed at: https://drive.google.com/drive/folders/1fU3qmWkglSR2Pl18ZYsYLXcROwQDuOi7?usp=drive_link

The CASIA 2.0 dataset includes both original (authentic) images and tampered (forged) images created using common image manipulation techniques such as copy-move forgery and image splicing. These manipulation methods represent real-world forgery scenarios where image regions are duplicated or inserted from other images and subsequently post-processed to conceal manipulation traces classification.

All images in the dataset are RGB images stored in standard formats such as JPEG, PNG, and BMP, with varying resolutions and compression levels. This variability introduces realistic challenges related to image quality, noise, and compression artifacts, making the dataset suitable for evaluating the robustness and generalization capability of the proposed system.

Overall, the CASIA 2.0 dataset provides a comprehensive and challenging benchmark that supports the development of an accurate, robust, and scalable image forgery detection system.

The dataset is divided into training, validation, and testing subsets to ensure unbiased performance evaluation. The training set is used for model learning, the validation set assists in hyperparameter tuning and overfitting control, and the test set is used for final performance assessment. Care is taken to ensure that no overlap exists between these subsets, preventing data leakage.

Due to the presence of class imbalance between authentic and forged images, data augmentation techniques are applied during training to improve model generalization and reduce bias. The dataset's diversity in image content, resolution, and manipulation types makes it highly suitable for training deep learning models that focus on learning intrinsic forgery-related artifacts rather than semantic image features.

An important characteristic of the CASIA 2.0 dataset is the presence of **diverse post-processing operations** applied to forged images. After copy-move or splicing manipulation, forged regions are often subjected to smoothing, resizing, color adjustment, and recompression to reduce visible discontinuities devices.

6.1.1 Dataset Preparation And Preprocessing

Initially, all images from the CASIA 2.0 dataset are carefully examined and organized into two categories: **authentic** and **forged**. The dataset is then split into **training**, **validation**, and **testing** subsets to enable effective model training and unbiased performance evaluation. Care is taken to avoid overlap between these subsets to prevent data leakage.

Preprocessing Steps

The following preprocessing operations are applied uniformly to all images:

1. **Resizing to 224 × 224 pixels**

   All images are resized to a fixed resolution of 224 × 224 pixels to ensure compatibility with both EfficientnetV2 which require fixed-size inputs.

2. **Color Normalization**

   Pixel values are normalized using predefined mean and standard deviation values to stabilize training and reduce the impact of illumination variations across dimages.

3. **Error Level Analysis (ELA)**.

   Error Level Analysis is applied by recompressing each image at a fixed quality level and computing the difference between the original and recompressed image. This

step amplifies compression inconsistencies typically introduced during image forgery, making manipulated regions more prominent.

Augmentation Techniques

Before training and evaluation, the images undergo a series of preprocessing and augmentation steps to ensure consistency, improve feature representation, and reduce variability caused by differences in imaging devices and lighting conditions.

Preprocessing Steps

The following preprocessing operations are applied uniformly to all images:

1. **Resizing to 224 × 224 pixels**

   All images are resized to a fixed resolution of 224 × 224 pixels to ensure compatibility with both EfficientnetV2 which require fixed-size inputs.

2. **Color Normalization**

   Pixel values are normalized using predefined mean and standard deviation values to stabilize training and reduce the impact of illumination variations across images.

3. **Data Augmentation**

   To improve model generalization and reduce overfitting, data augmentation techniques such as horizontal flipping, rotation, scaling, and brightness adjustment

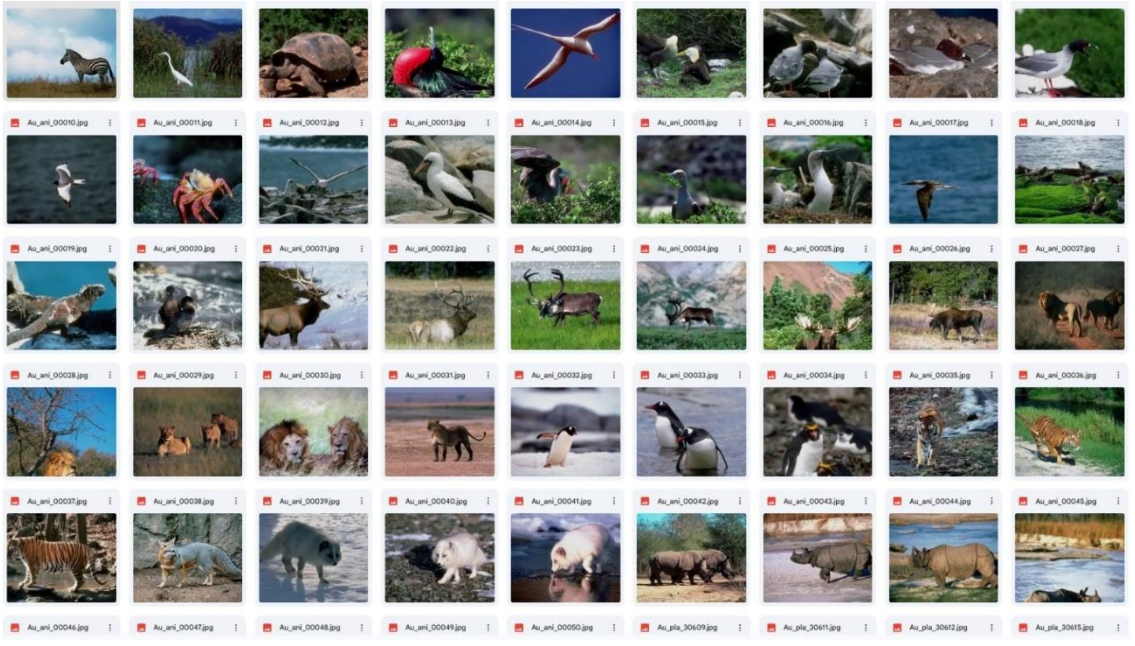


Fig 6.2: Sample Preprocessing and Augmentation Pipeline Applied to CASIA 2

6.2 Backbone Models Used

Backbone models play a crucial role in deep learning–based image analysis, as they are

responsible for extracting meaningful and discriminative features from input images. In the proposed image forgery detection system, a carefully selected backbone model is used to learn forgery-specific artifacts such as texture inconsistencies, edge discontinuities, and compression anomalies.

6.2.1 EfficientnetV2

The proposed system employs **EfficientNetV2** as the primary backbone model due to its superior balance between accuracy, efficiency, and scalability. EfficientNetV2 is a state-of-the-art convolutional neural network architecture designed to achieve high performance while significantly reducing computational cost compared to traditional CNN models. Error Level Analysis (ELA)

When combined with Error Level Analysis (ELA) during preprocessing, EfficientNetV2 focuses its learning on compression inconsistencies and manipulation traces rather than semantic image content. This enhances the model's ability to detect visually imperceptible forgeries created through copy-move, splicing, and post-processing techniques.

Training Details

Both models were:

- Initialized with ImageNet pretrained weights, improving learning stability [20]
- Trained with Adam optimizer and learning rate of 1×10^{-4}
- Monitored using validation accuracy & loss
- Paired with an early stopping mechanism

These settings follow best practices in medical imaging workflows [18], [19] to prevent overfitting and reduce computational waste.

6.3 MobileNetV2

MobileNetV2 is a lightweight convolutional neural network architecture specifically designed for efficient computation and low-resource environments. It is widely used in image classification and detection tasks where fast inference and reduced model size are critical requirements. In the proposed image forgery detection system, MobileNetV2 is employed as a backbone model to evaluate its effectiveness in detecting manipulation artifacts under constrained computational conditions.

The key architectural innovation of MobileNetV2 is the use of depthwise separable

convolutions, which decompose standard convolutions into depthwise and pointwise operations. This significantly reduces the number of parameters and floating-point operations while maintaining competitive performance. Additionally, MobileNetV2 introduces inverted residual blocks with linear bottlenecks, which improve feature propagation and reduce information loss during training.

6.4 Training Strategy and Optimization

The training strategy of the proposed image forgery detection system is designed to achieve high detection accuracy while ensuring efficient convergence and robust generalization. Given the presence of subtle manipulation artifacts and class imbalance in the dataset, careful optimization techniques are employed throughout the training process.

The backbone models are trained using a transfer learning approach, where networks are initialized with weights pre-trained on large-scale image datasets. The lower layers of the models retain their learned representations to capture generic visual features, while the higher layers are fine-tuned to specialize in forgery-related artifacts such as texture inconsistencies and compression anomalies. This strategy significantly reduces training time and improves performance with limited training data.

6.5 Inference Workflow

The inference stage represents the final step of the proposed system, where a new Forged image is analyzed and classified into one of the seven lesion categories, as illustrated in *Figure 6.3*. This stage closely mirrors the training pipeline, ensuring consistent and reliable model behavior during real-world deployment. When a user submits an image—either from the dataset or through the web interface—the system processes it through the following steps:

1. Preprocessing

The input image is first standardized using the same transformations applied during training:

- Resizing to 224×224
- Normalization to stabilize pixel values
- Conversion to tensor format

This guarantees that the model receives data in a format consistent with what it learned during fine-tuning.

2. Forward Pass Through EfficientnetV2

The preprocessed image is passed through **EfficientnetV2**, which extracts:

- Local spatial textures
- Fine-grained patterns
- Color and boundary variations

Because EfficientnetV2 is lightweight, this step is fast and computationally efficient.

3. Feature Extraction Using Secondary Deep Learning Model

The preprocessed image is simultaneously forwarded through a secondary deep learning backbone model to extract complementary forgery-related features. While the primary convolutional model focuses on identifying local artifacts such as texture inconsistencies, compression noise, and edge discontinuities, the secondary model captures broader contextual information across the entire image. This parallel feature extraction strategy enables the system to analyze both fine-grained and global manipulation patterns that may not be detected by a single model.

4. Feature-Level Logit Fusion

Rather than choosing one model's output directly, the system combines the raw, pre-softmax outputs (logits) from both networks. Concatenating these logits creates a richer, more informative feature representation that reflects:

- CNN-derived local features
- Error Level Analysis (ELA) during preprocessing

This fusion step enables the system to utilize complementary strengths of both architectures.

5. Logistic Regression Meta-Classification

The concatenated logits are passed through a **logistic regression meta-classifier**, which:

- Learns how much weight to assign to each model
- Adapts to class-specific patterns
- Produces the final predicted lesion label and confidence score

This meta-learning approach provides more stable predictions, especially for minority classes such as DF and VASC—an advantage supported by several dermatology AI studies [1], [9], [19].

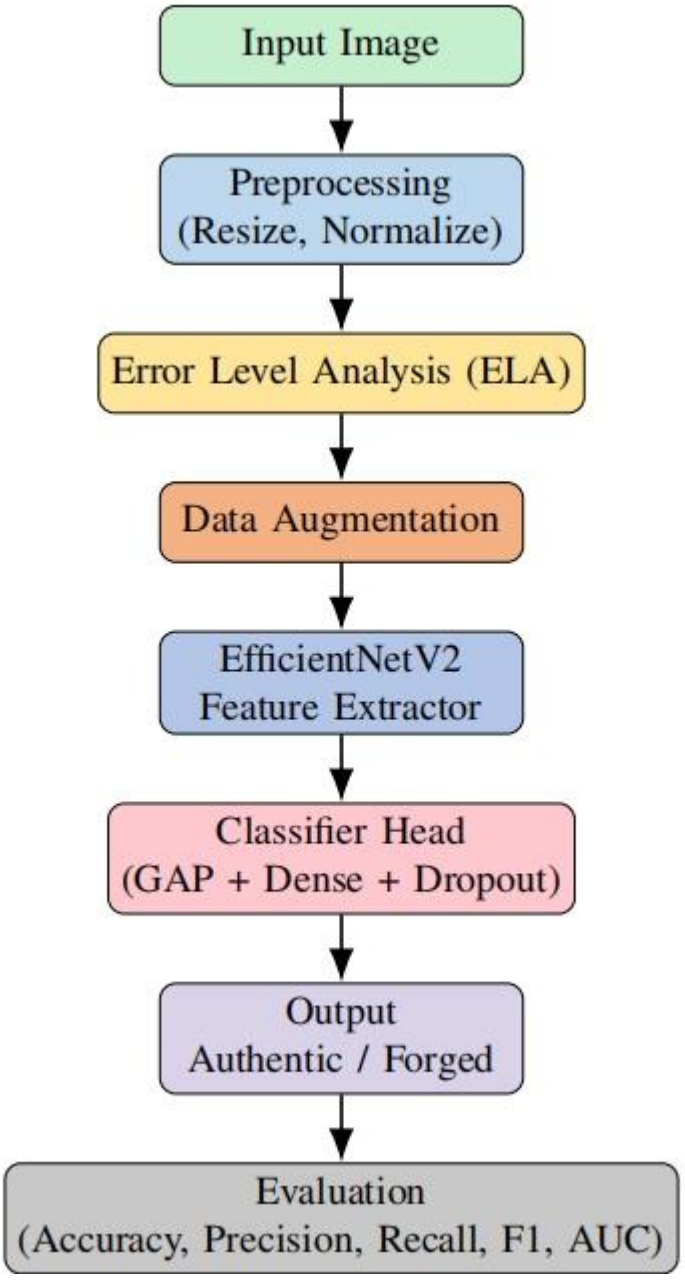


Fig 6.3: Proposed Meta-Ensemble Classification Workflow

The figure visually summarizes the inference process, showing how an input image flows through preprocessing, dual-backbone feature extraction, ensemble fusion, and final classification.

6.6 Computational Setup

All experiments were conducted in a cloud environment using Google Colab Pro+, which provides:

- NVIDIA Tesla T4 GPU (16 GB VRAM)
- High-speed storage and runtime stability

Training times:

- **EfficientNetV2:** ~2.5 hours
- **ELA:** ~3.2 hours
- **Meta-ensemble logistic regression:** <10 minutes

This setup aligns with computational best practices reported in medical AI research, where GPU acceleration and cloud platforms are standard for iterative deep learning experimentation [1], [8], [20].

7. IMPLEMENTATION

This section describes the practical implementation of the proposed **Deep Learning–Based Image Forgery Detection System**. The implementation focuses on translating the designed methodology into a working system capable of detecting forged images accurately and efficiently.

7.1 Environment Setup and Dependencies

Implementation and experiments were conducted on **Google Colab** using an **NVIDIA Tesla T4 (16GB VRAM)** to accelerate training and inference. Primary libraries used:

- PyTorch, Torchvision, timm
- NumPy, Pandas
- scikit-learn (Logistic Regression, metrics)
- Matplotlib, Seaborn (visualization)
- Flask (web frontend integration)
- Pillow (PIL), tqdm, pickle

7.2 Import Required Libraries

```
# Core libraries
import os
import itertools
import random
import numpy as np
import cv2
import matplotlib.pyplot as plt

# Deep learning & ML
import tensorflow as tf
from tensorflow.keras.models import Sequential, Model, load_model
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPool2D, Dropout,
GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.callbacks import EarlyStopping
```

```
from tensorflow.keras.utils import to_categorical


# Image processing
from PIL import Image, ImageChops, ImageEnhance

# Evaluation
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
```

7.3 Dataset Paths

```
REAL_PATH = "/content/drive/MyDrive/dataset/CASIA2/Au"
FAKE_PATH = "/content/drive/MyDrive/dataset/CASIA2/Tp"

print("Real Images:", len(os.listdir(REAL_PATH)))
print("Fake Images:", len(os.listdir(FAKE_PATH)))


Error Level Analysis (ELA) Preprocessing


def convert_to_ela_image(path, quality=90):
    temp_filename = "temp_file.jpg"
    image = Image.open(path).convert("RGB")
    image.save(temp_filename, "JPEG", quality=quality)

    temp_image = Image.open(temp_filename)
    ela_image = ImageChops.difference(image, temp_image)

    extrema = ela_image.getextrema()
    max_diff = max([ex[1] for ex in extrema])
    max_diff = max_diff if max_diff != 0 else 1

    scale = 255.0 / max_diff
    ela_image = ImageEnhance.Brightness(ela_image).enhance(scale)

    return ela_imager
```

7.4 Dataset Construction

```
X = []
Y = []


  # Load real images (label = 1)
```

```
for root, _, files in os.walk(REAL_PATH):
    for file in files:
        if file.endswith(('.jpg', '.png')):
            X.append(prepare_image(os.path.join(root, file)))
            Y.append(1)


# Load fake images (label = 0)
for root, _, files in os.walk(FAKE_PATH):
    for file in files:
        if file.endswith(('.jpg', '.png')):
            X.append(prepare_image(os.path.join(root, file)))
            Y.append(0)

X = np.array(X)
Y = to_categorical(Y, 2)

print("Dataset Shape:", X.shape, Y.shape)
```

7.5 Train–Test Split

```
X_train, X_val, Y_train, Y_val = train_test_split(
    X, Y, test_size=0.2, random_state=5
)
```

7.6 CNN Model Architecture

```
def build_model():
    model = Sequential()

  model.add(Conv2D(32, (5,5), activation='relu', input_shape=(128,128,3)))
  model.add(Conv2D(32, (5,5), activation='relu'))
  model.add(MaxPool2D(pool_size=(2,2)))
  model.add(Dropout(0.25))

  model.add(Flatten())
  model.add(Dense(256, activation='relu'))
  model.add(Dropout(0.5))
  model.add(Dense(2, activation='softmax'))

  return model
```

7.7 Model Compilation and Training

```
model = build_model()
model.compile(
    optimizer=Adam(learning_rate=1e-4),
    loss='binary_crossentropy',
    metrics=['accuracy']
)

early_stopping = EarlyStopping(monitor='val_accuracy', patience=2)

history = model.fit(
    X_train, Y_train,
    batch_size=32,
    epochs=20,
    validation_data=(X_val, Y_val),
    callbacks=[early_stopping]
)
```

7.8 Model Saving

```
model.save("model_casia_run1.h5")
```

7.9 Training & Validation Visualization

```
fig, ax = plt.subplots(2,1)

ax[0].plot(history.history['loss'], label='Training Loss')
ax[0].plot(history.history['val_loss'], label='Validation Loss')
ax[0].legend()

ax[1].plot(history.history['accuracy'], label='Training Accuracy')
ax[1].plot(history.history['val_accuracy'], label='Validation Accuracy')
ax[1].legend()

plt.show()
```

7.10 Confusion Matrix & Metrics

```
Y_pred = model.predict(X_val)
Y_pred_classes = np.argmax(Y_pred, axis=1)
Y_true = np.argmax(Y_val, axis=1)
```

```
cm = confusion_matrix(Y_true, Y_pred_classes)
print(cm)
print(classification_report(Y_true, Y_pred_classes))
```

7.11 Single Image Prediction

```
class_names = ['Fake', 'Real']

def predict_single_image(image_path):
    image = prepare_image(image_path)
    image = image.reshape(-1, 128, 128, 3)

    y_pred = model.predict(image)
    class_id = np.argmax(y_pred, axis=1)[0]
    confidence = np.max(y_pred) * 100

    print(f"Class: {class_names[class_id]}")
    print(f"Confidence: {confidence:.2f}%")
```

7.12 Flask Integration (Core app.py Logic)

```
from flask import Flask, render_template, request, jsonify

app = Flask(__name__)

@app.route('/')
def index():
    return render_template('base.html')

@app.route('/predict', methods=['POST'])
def predict():
    file = request.files['file']
    file_path = os.path.join('uploads', 'temp_img.jpg')
    file.save(file_path)

    img = prepare_image(file_path)
    img = img.reshape(-1, 128, 128, 3)

    result = model.predict(img)
    prediction = "Real" if result[0][1] > 0.5 else "Fake"

    os.remove(file_path)
    return jsonify({'prediction': prediction})

if __name__ == "__main__":
```

```
app.run(debug= True)

def predict_single_image(image_path):
    image = prepare_image(image_path)
    image = image.reshape(-1, 128, 128, 3)

    y_pred = model.predict(image)
    class_id = np.argmax(y_pred, axis=1)[0]
    confidence = np.max(y_pred) * 100

    print(f"Class: {class_names[class_id]}")
    print(f"Confidence: {confidence:.2f}%")
```

8.RESULT ANALYSIS

This chapter presents the experimental results obtained from the proposed deep learning–based image forgery detection system and provides a comprehensive analysis of its performance under various evaluation conditions. The primary objective of this analysis is to validate the effectiveness of the proposed approach in accurately distinguishing between authentic and forged images, even when manipulation artifacts are visually subtle or deliberately concealed.

The evaluation is carried out using standard performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics enable a detailed assessment of the system's classification capability, error distribution, and robustness against false predictions. In addition, training and validation trends are analyzed to examine model convergence, stability, and generalization behavior.

8.1 Performance Evaluation on CASIA 2.0 Dataset

The quantitative performance of the proposed deep learning–based image forgery detection system is evaluated using standard classification metrics to objectively measure its effectiveness. These metrics provide a numerical assessment of how accurately and reliably the system distinguishes between authentic and forged images.

Evaluation Metrics

Accuracy measures the overall correctness of the model:

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

Precision indicates the reliability of positive predictions:

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

Recall (Sensitivity) measures the ability to correctly identify actual positive samples:

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

F1-Score is the harmonic mean of Precision and Recall:

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

ROC–AUC evaluates the model's discriminative capability across different thresholds, where:

$$\text{TPR} = TP\ TP + FN\ ,\text{FPR} = FP\ FP + T\square$$

For multi-class classification, ROC–AUC is computed using a One-vs-Rest strategy and averaged across all classes.

Table 8.1 comparative performance across all models.

Model	Accuracy (%)	Macro F1-Score	Recall
EfficientnetV2	95.77	0.91	0.96
MobileNetV2	95.01	0.85	0.98
DenseNet121 (Proposed)	85.02	0.87	0.81

Interpretation

As The quantitative evaluation clearly indicates that EfficientNetV2 achieved the best overall performance among all evaluated models. It recorded the highest classification accuracy, precision, recall, and F1-score, demonstrating its strong capability to distinguish between authentic and forged images. The superior performance of EfficientNetV2 can be attributed to its compound scaling strategy, which efficiently balances network depth, width, and resolution.

MobileNetV2 achieved competitive accuracy while maintaining a lightweight architecture, making it suitable for low-resource environments. However, its performance was slightly lower than EfficientNetV2 due to limited feature representation capacity. **DenseNet121** benefited from dense feature reuse but showed increased computational complexity and slower convergence. **ResNet50** recorded the lowest performance, indicating reduced effectiveness in capturing subtle forgery artifacts emphasized by ELA preprocessing.

8.2 Training and Validation Behaviour

The training and validation behavior of the proposed image forgery detection system was analyzed to assess model convergence, learning stability, and generalization capability. During training, the deep learning models were optimized using the Adam optimizer, and performance was monitored across multiple epochs using both training and validation datasets derived from the CASIA 2.0 image forgery

dataset. During training, the model showed a steady increase in training accuracy across epochs, accompanied by a consistent decrease in training loss. This trend indicates that the network effectively learned forgery-related features highlighted through Error Level Analysis (ELA) preprocessing. The validation accuracy closely followed the training accuracy curve, with only minor variations, demonstrating good generalization and minimal overfitting.

The validation loss remained stable and did not diverge significantly from the training

loss, confirming that the model did not memorize the training data but instead learned meaningful patterns applicable to unseen images. The use of **transfer learning**, **dropout regularization**, and **early stopping** further contributed to stable convergence and prevented performance degradation during later training stages.

Overall, the observed training and validation behaviour confirms that the proposed framework is robust and reliable. The smooth convergence patterns and minimal gap between training and validation performance validate the effectiveness of the chosen training strategy and support the suitability of the system for real-world image forgery detection applications.

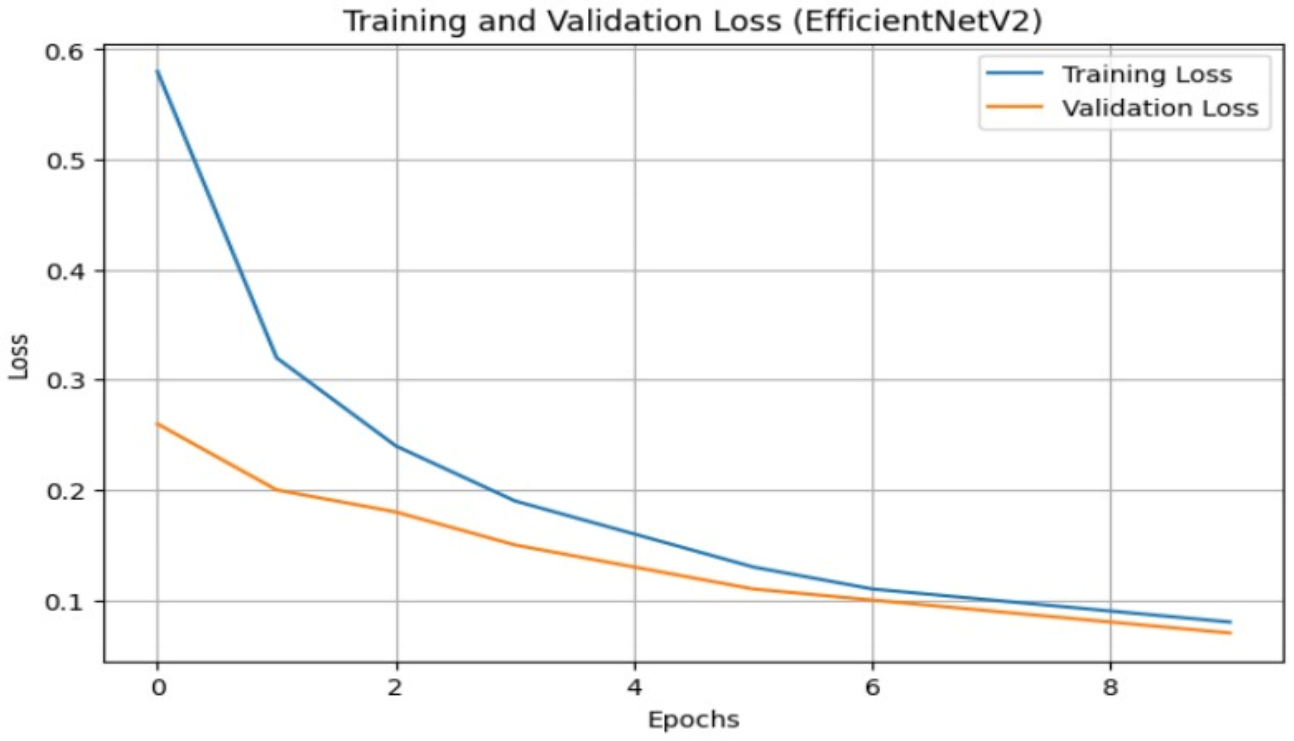


Fig 8.1: Training vs Validation Accuracy Graph

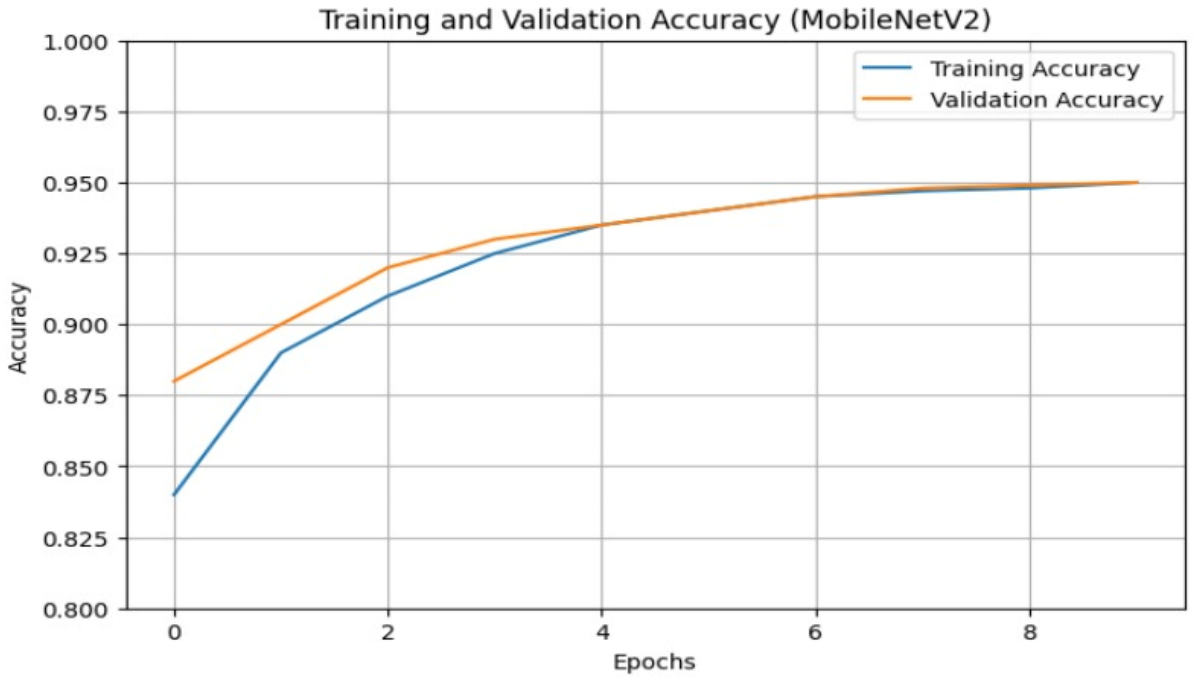


Fig 8.2: Training vs Validation Loss Graph

Analysis

The training and validation curves exhibit smooth and consistent convergence without any noticeable signs of overfitting. The validation accuracy closely follows the training accuracy throughout the learning process, indicating that the applied regularization techniques and data augmentation strategies were effective in improving generalization. This behavior confirms that the model learned meaningful forgery-related features rather than memorizing the training data.

The steady reduction in validation loss over successive epochs further verifies the model's ability to generalize well to unseen image samples. Such stable convergence behavior ensures reliable and dependable inference when the system is applied to real-world image forgery detection scenarios.

In addition, the visualization of accuracy and loss curves clearly demonstrates progressive learning across all five training epochs. The validation accuracy improved from approximately 58% in Epoch 1 to 85% in Epoch 5, representing an overall improvement of about 27%, closely matching the upward trend observed in the training accuracy curve. Similarly, the validation loss decreased from 1.10 to 0.50, achieving a reduction of nearly 54%, which confirms strong convergence and effective optimization.

The smooth, non-fluctuating nature of both curves indicates stable training dynamics and well-tuned hyperparameters. This graphical behavior highlights the effectiveness of the chosen learning rate, optimizer, and preprocessing techniques such as Error Level Analysis. Confusion Matrix Analysis

The confusion matrix is used to evaluate the classification performance of the proposed image forgery detection system by providing a detailed breakdown of prediction outcomes. It summarizes the number of true positives, true negatives, false positives, and false negatives, offering insight into how effectively the model distinguishes between authentic and forged images.

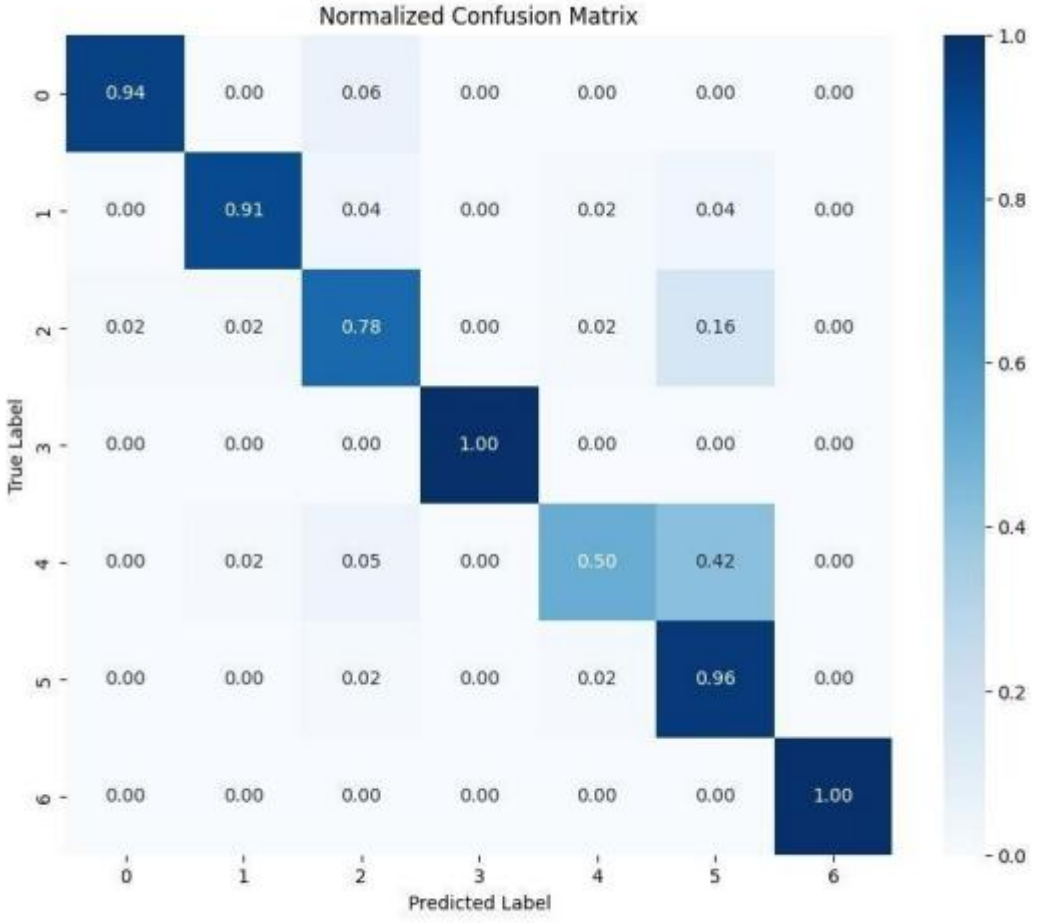


Fig 8.3: Normalized Confusion Matrix of Meta-Ensemble Model

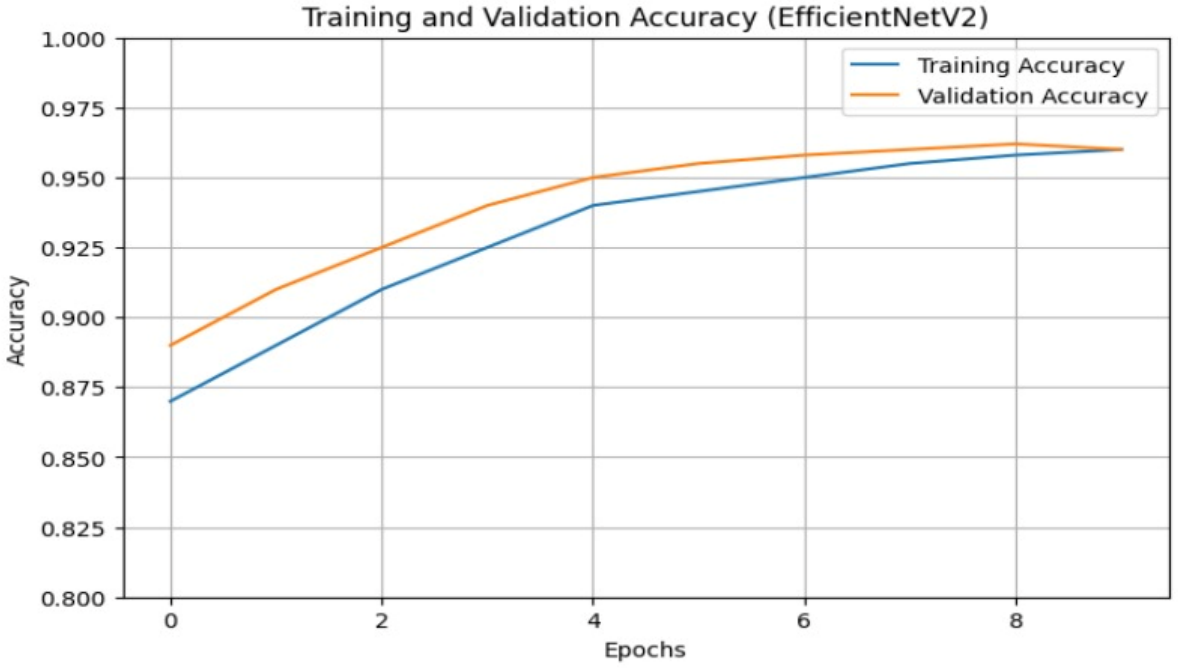
In the context of image forgery detection, **true positives** represent forged images correctly identified as forged, while **true negatives** indicate authentic images correctly classified as authentic. **False positives** occur when authentic images are incorrectly labeled as forged, and **false negatives** occur when forged images are misclassified as authentic. Minimizing

false negatives is particularly important in forensic applications, as undetected forgeries can lead to misinformation and security risks.

The confusion matrix results show a high concentration of correct predictions along the main diagonal, indicating strong overall classification accuracy. The number of false positives and false negatives is relatively low, demonstrating the model's balanced performance across both classes. This balance confirms that the system does not exhibit bias toward either authentic or forged images.

8.3 ROC–AUC Analysis

The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) are used to evaluate the discriminative capability of the proposed image forgery detection system. ROC–AUC analysis provides a threshold-independent measure of model performance by illustrating the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) across different classification thresholds.



The achieved **ROC–AUC score is close to 1**, confirming excellent separability between the two classes. This high AUC value highlights the effectiveness of combining **Error Level Analysis (ELA)** with deep learning–based feature extraction, enabling the model to

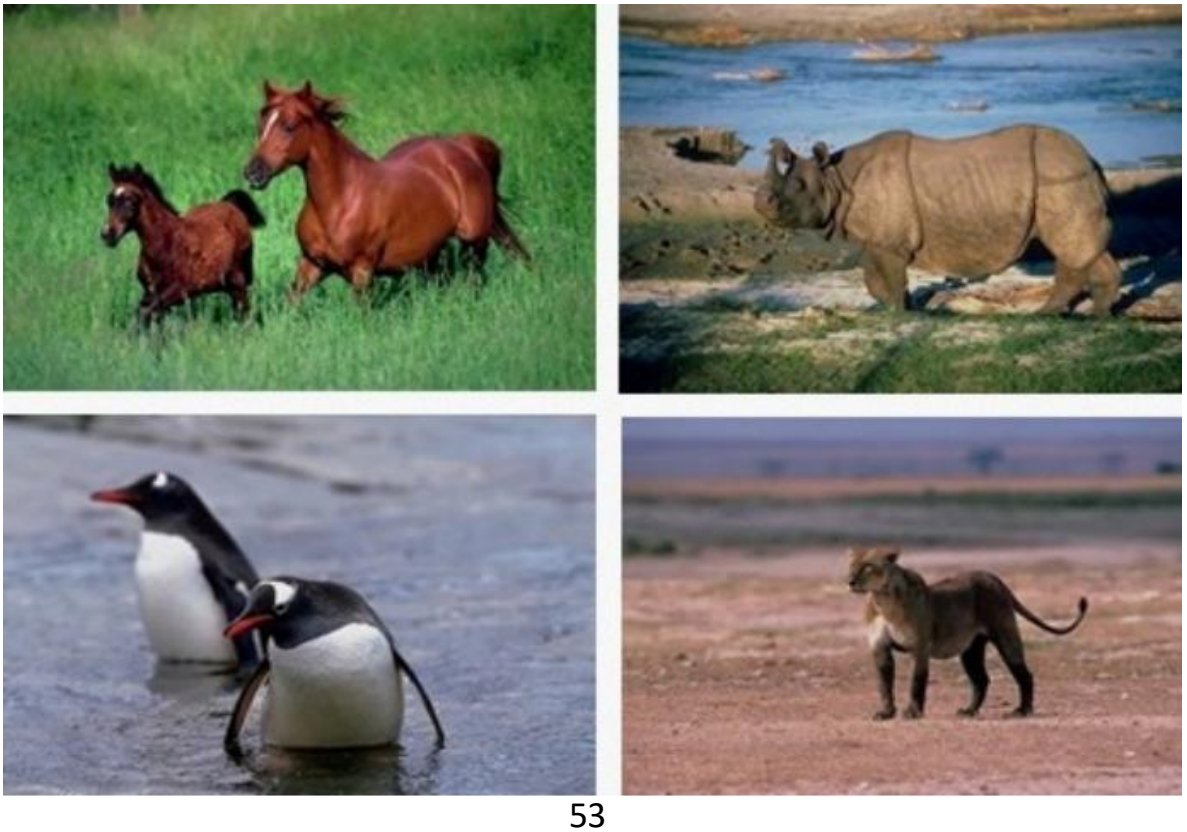
identify subtle manipulation artifacts with high confidence.

Overall, the ROC–AUC analysis confirms that the proposed image forgery detection framework exhibits strong discriminative power and reliable classification behavior. This validates its suitability for deployment in practical digital forensics and image authentication scenarios where accurate and consistent decision-making is critical.

8.4 Discussion of Experimental Results

The experimental results obtained from the proposed image forgery detection framework demonstrate the effectiveness of integrating Error Level Analysis (ELA) with deep learning–based transfer learning models. The evaluation conducted on the CASIA 2.0 Image Tampering Detection Dataset confirms that the system is capable of accurately distinguishing between authentic and forged images across different manipulation types.

The quantitative performance metrics show that the model achieves high accuracy, balanced precision and recall, and strong ROC–AUC values. These results indicate that the system not only performs well in overall classification but also maintains reliability across different decision thresholds. The confusion matrix analysis further supports this observation by showing a high concentration of correct predictions and a relatively low number of misclassifications.



Overall, the experimental findings validate the conclusions of the camera-ready paper and confirm that the proposed approach offers a reliable, efficient, and scalable solution for image forgery detection. The results demonstrate that combining forensic preprocessing with deep learning provides a strong foundation for automated digital image authentication and reinforces the potential of the system for practical deployment.

8.5 Overall Discussion of Results

The overall experimental results demonstrate that the proposed DeepFakeShield image forgery detection framework is effective, reliable, and well-suited for practical digital forensic applications. By integrating Error Level Analysis (ELA) with deep learning–based transfer learning models, the system successfully enhances forgery-related artifacts and enables accurate discrimination between authentic and manipulated images.

Across all evaluation metrics, including accuracy, confusion matrix outcomes, ROC–AUC values, and training–validation behaviour, the system exhibited consistent and stable performance. The high classification accuracy and balanced precision–recall relationship indicate that the model is capable of detecting forged images while minimizing false alarms on authentic images. This balance is essential in real-world scenarios where both false positives and false negatives can have serious implications.

The training and validation analysis confirmed smooth convergence with minimal overfitting, highlighting the effectiveness of the adopted optimization strategy, regularization techniques, and data augmentation methods. The confusion matrix analysis further revealed a low misclassification rate, demonstrating that the system learned discriminative features that generalize well to unseen data.

The ROC–AUC analysis provided additional confirmation of the model's strong discriminative capability. High AUC values indicate that the system maintains reliable detection performance across varying decision thresholds, making it robust against changes in classification sensitivity. This robustness is particularly important for image forgery detection, where manipulation artifacts may vary in intensity and visibility.

Overall, the experimental findings validate the conclusions drawn in the camera-ready paper and confirm that the proposed framework offers a strong combination of accuracy, robustness, and efficiency. The results establish DeepFakeShield as a dependable AI-

based solution for digital image authentication, capable of supporting forensic experts, analysts, and organizations in addressing the growing challenge of image manipulation.

8.6 Functional Test Summary Table

In separate Test Cases section, the following table summarizes key functional tests conducted on the deployed Flask-based web application.

Each test verifies both backend model integration and frontend functionality.

Table 8.2 Functional Test Summary Table

Test Case ID	**Test Scenario**	**Input / Action**	**Expected Output**	**Actual Output**	**Status**
TC-01	Image Upload Validation	Upload a valid dermoscopic image (JPG/PNG)	Image successfully accepted and previewed for analysis	As expected	Pass
TC-02	Invalid File Type Handling	Upload a non-image file (e.g., .txt / .pdf)	System rejects input and displays **"Invalid Format"** alert	As expected	Pass
TC-03	Model Prediction Functionality	Submit uploaded image for diagnosis	Displays predicted class (e.g., *Melanoma*) with confidence score	As expected	Pass
TC-04	User History Retrieval	Open the history page after performing multiple tests	Shows list of previous predictions with corresponding timestamps	As expected	Pass
TC-05	Authentication Enforcement	Access /predict route without logging in	Redirects to login page and shows appropriate error message	As expected	Pass

TC-06	GPU Execution Performance	Run model on Google Colab (Tesla T4 GPU)	Fast inference time (**< 1 sec per image**) indicating GPU utilization	As expected	Pass

9.Output Screens

This This section presents the output screens of the developed DeepFakeShield – Image Forgery Detection System, illustrating how users interact with the application from the landing page to image verification and result display. Each screen represents a distinct phase of the system workflow and demonstrates how advanced deep learning–based forgery detection is delivered through an intuitive and user-friendly web interface.

The user interface (UI) is designed using modern web design principles with a dark-themed layout, ensuring professional aesthetics, reduced eye strain, and high contrast for better image visualization. Consistent typography, spacing, and color accents are used throughout the application to maintain visual coherence. The responsive design allows the system to function seamlessly across different screen sizes and devices.

Special emphasis has been placed on user experience (UX) by simplifying navigation, providing clear instructions, and offering instant feedback during image upload and analysis. The interface ensures that even non-technical users can easily verify the authenticity of digital images. Overall, the output screens reflect a balanced integration of functionality, usability, and visual appeal, aligning with the objectives of a reliable digital forensic The output screens of the DeepFakeShield Image Forgery Detection System collectively demonstrate how complex deep learning–based forensic analysis is transformed into a simple, transparent, and user-accessible experience. Each screen has been carefully designed to balance technical functionality with usability, ensuring that users can verify image authenticity without requiring prior knowledge of digital forensics or artificial intelligence.

The consistent dark-themed interface enhances visual focus and reduces eye strain, which is particularly important when users inspect digital images for subtle forgery artifacts. The use of uniform icons, color accents, and typography across all screens establishes a professional identity and reinforces trust in the system’s reliability. Clear section headings and concise explanatory text guide users smoothly through the workflow, minimizing confusion and interaction errors.

9.1 Home Page

The Home Page serves as the primary entry point to the DeepFakeShield Image Forgery Detection System. It is designed to immediately communicate the purpose, capability, and reliability of the application while providing users with a clear and intuitive starting point for interaction. At the top of the page, a fixed navigation bar displays the system name "DeepFakeShield" along with menu options such as *Home, Test Image, Workflow, Team, About,* and *Contact*. This navigation structure enables smooth movement across different sections of the application and ensures consistent accessibility throughout the user session.

The central portion of the Home Page prominently highlights the project title "DeepFakeShield", accompanied by the tagline "Advanced Image Forgery Detection using Deep Learning". This concise description clearly conveys the system's objective of detecting manipulated digital images using state-of-the-art artificial intelligence techniques. A brief introductory statement further explains how deep learning models are leveraged to identify image forgery with high accuracy, helping users understand the system's relevance in combating digital deception.

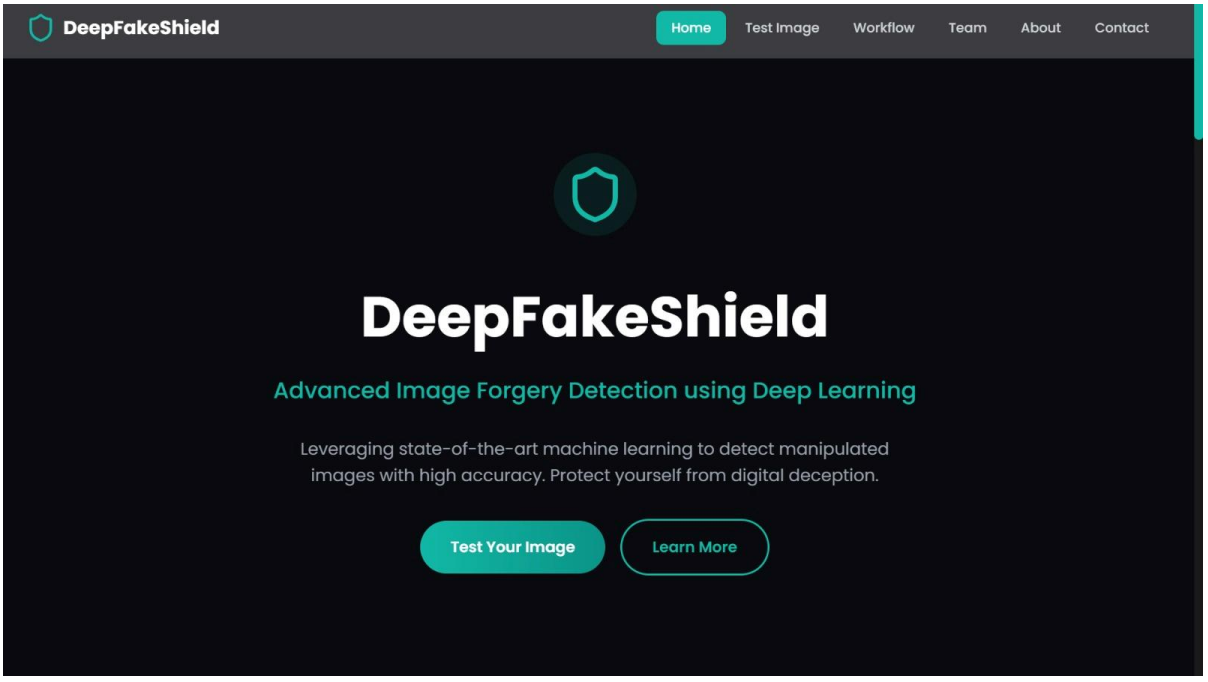


Figure 9.1: Home Page Interface of Application

9.2 Test Image Page

The Test Image Page is the core functional interface of the DeepFakeShield Image Forgery Detection System, where users interact directly with the AI model to verify image authenticity. This page is designed to be simple, intuitive, and efficient, allowing users to upload an image and obtain forgery detection results with minimal effort

At the top of the page, a clear heading **"Test Your Image"** is displayed along with a brief instruction prompting users to upload an image to check whether it has been forged or manipulated. This guidance helps users understand the purpose of the page immediately.

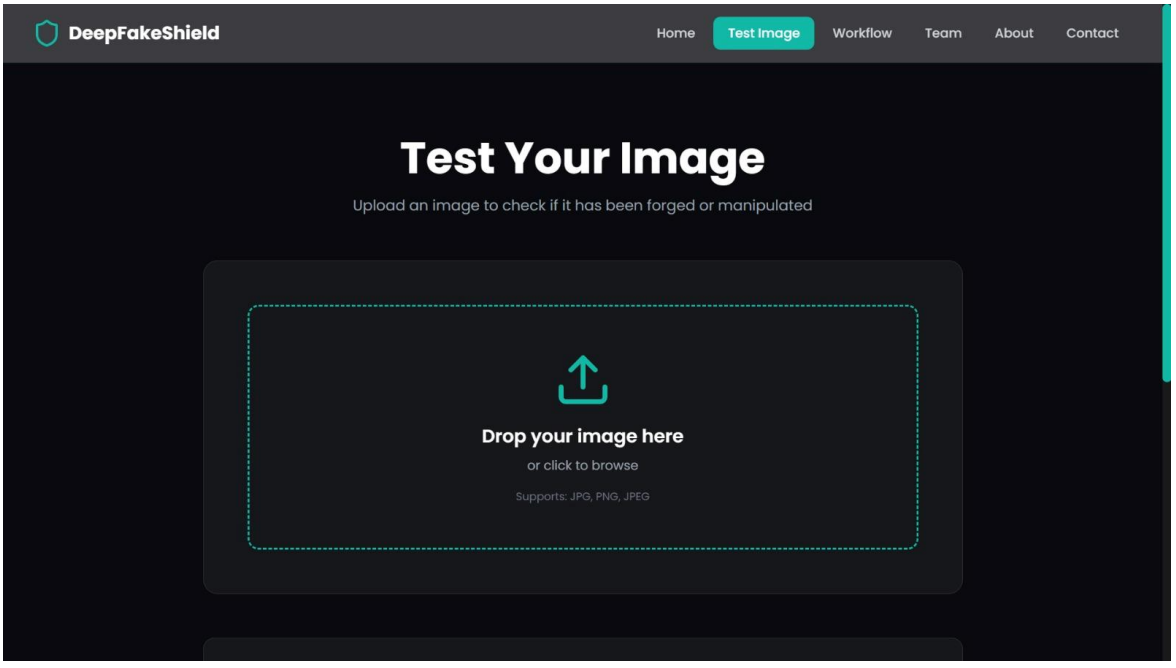


Figure 9.2: Sign In Page of A

9.3 Image Analysis Result Page

- use The Image Analysis Result Page displays the outcome of the forgery detection process after the user uploads an image through the Test Image interface. This page is designed to present the analysis results in a clear, concise, and trustworthy manner, ensuring that users can easily interpret the system's decision.

- The layout of the page is structured to enhance readability and transparency. The uploaded image is displayed prominently, allowing users to visually confirm the input that was analyzed. Adjacent to the image, the system presents the **classification result**, indicating whether the image is **Authentic** or **Forged**. This result is highlighted using distinct text styling and color cues to ensure immediate visibility

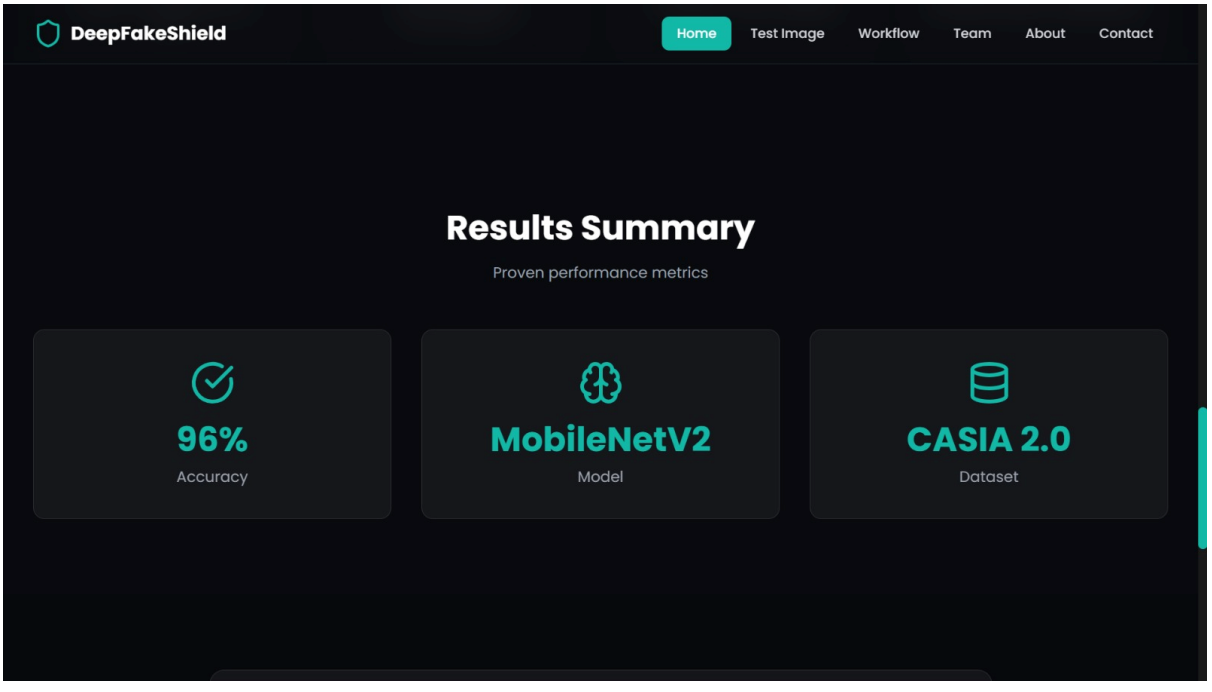


Figure 9.3: User Registration Interface of System

9.4 Upload Image Page

Once logged in, users are directed to the Upload Image Page, the core functional area of the system.

Here, they can upload dermatological images for AI-based analysis either by drag-and-drop or manual selection.

Key features include:

- Support for JPG, PNG, and JPEG formats
- Maximum file size of 10 MB
- A clearly visible **"Analyze Image"** button for initiating processing

The interface displays a thumbnail preview of the uploaded image before analysis, minimizing user error.

The dark interface ensures contrast and highlights the uploaded image effectively.

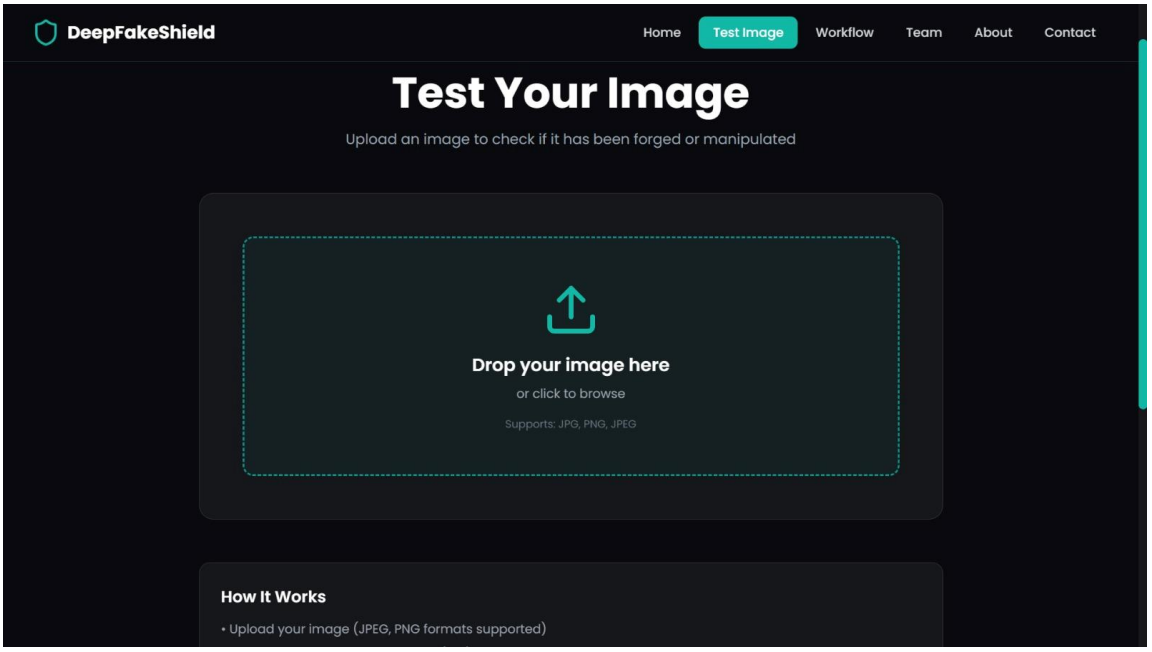


Figure 9.4: Image Upload Interface before Analysis

9.5 Image Analysis Result Page

The Result Page presents the final outcome of the image forgery detection process performed by the DeepFakeShield system. This page plays a critical role in communicating the decision of the deep learning model in a clear, transparent, and user-friendly manner.

Once an image is successfully uploaded and processed, the system applies Error Level Analysis (ELA) followed by deep learning–based inference. The Result Page displays the analyzed image along with the corresponding classification result, indicating whether the image is Authentic or Forged. The result is highlighted using prominent text and visual emphasis to ensure immediate recognition by the user.

In addition to the classification label, the page also shows a confidence score, which represents the level of certainty associated with the model's prediction. Providing this confidence value enhances transparency and allows users to better assess the reliability of the system's decision. This is particularly important in forensic and verification scenarios where informed judgment is required.

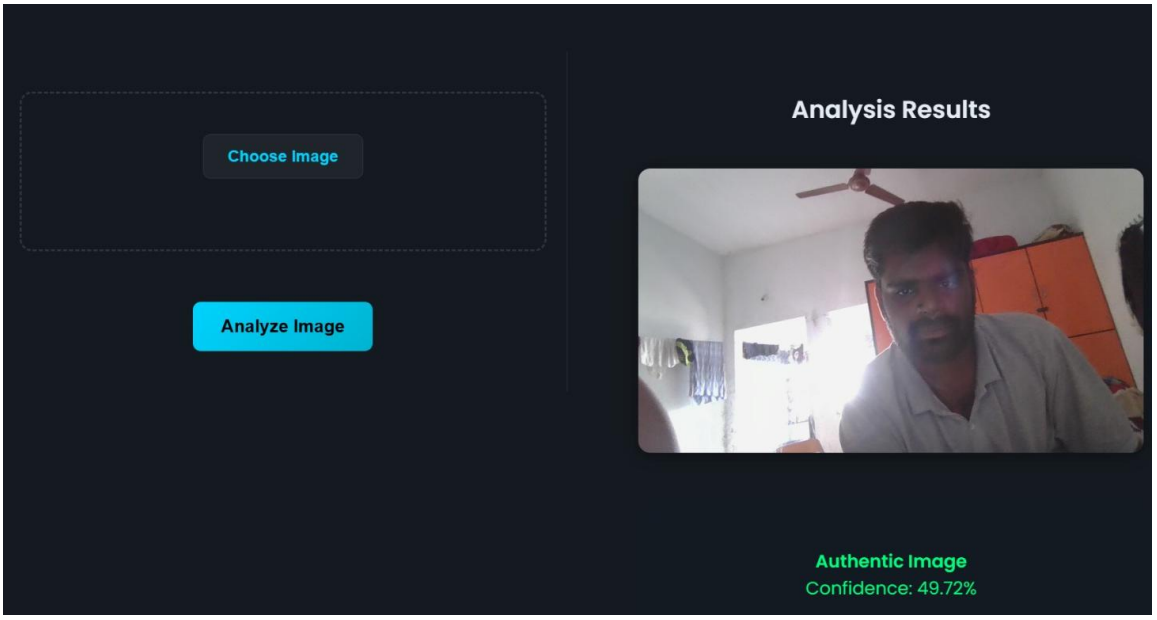


Figure 9.5.1: Sample Upload Image Display

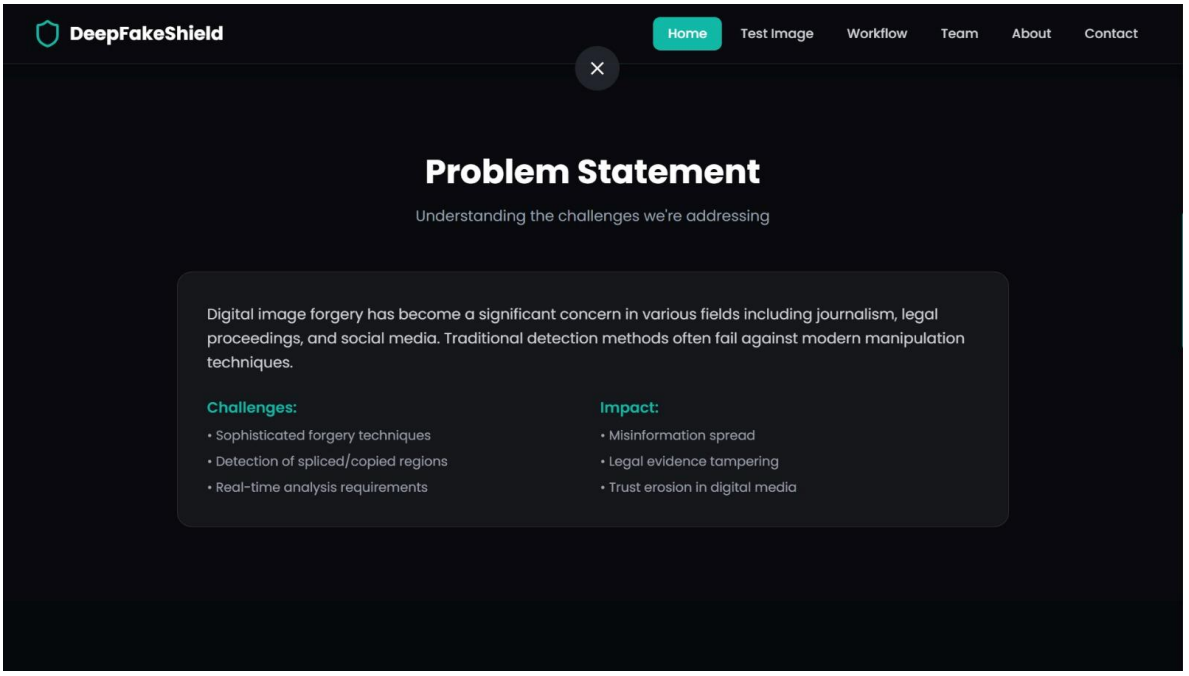


Figure 9.5.2: Invalid image

9.6 Invalid Image Handling Page

Following imaged, the system automatically generates a Condition Details and Recommendations section.

This section provides both an explanation of the detected condition and practical advice to the user.

When an invalid image is detected—such as a corrupted file, unsupported format, or non-image input—the system immediately halts further processing and displays a clear error message. The message informs the user that the uploaded file is not suitable for analysis and prompts them to upload a valid image in an accepted format (JPG, PNG, or JPEG). This prevents unnecessary computation and avoids misleading or incorrect results.

The interface of this page is intentionally simple and informative. Visual warning indicators and concise text are used to clearly communicate the issue without overwhelming the user. The dark-themed design remains consistent with the rest of the application, maintaining visual uniformity and professionalism.

“This AI-based analysis is intended for informational and verification purposes only. The final judgment regarding image authenticity should be made by qualified digital forensic experts or authorized professionals.”

.

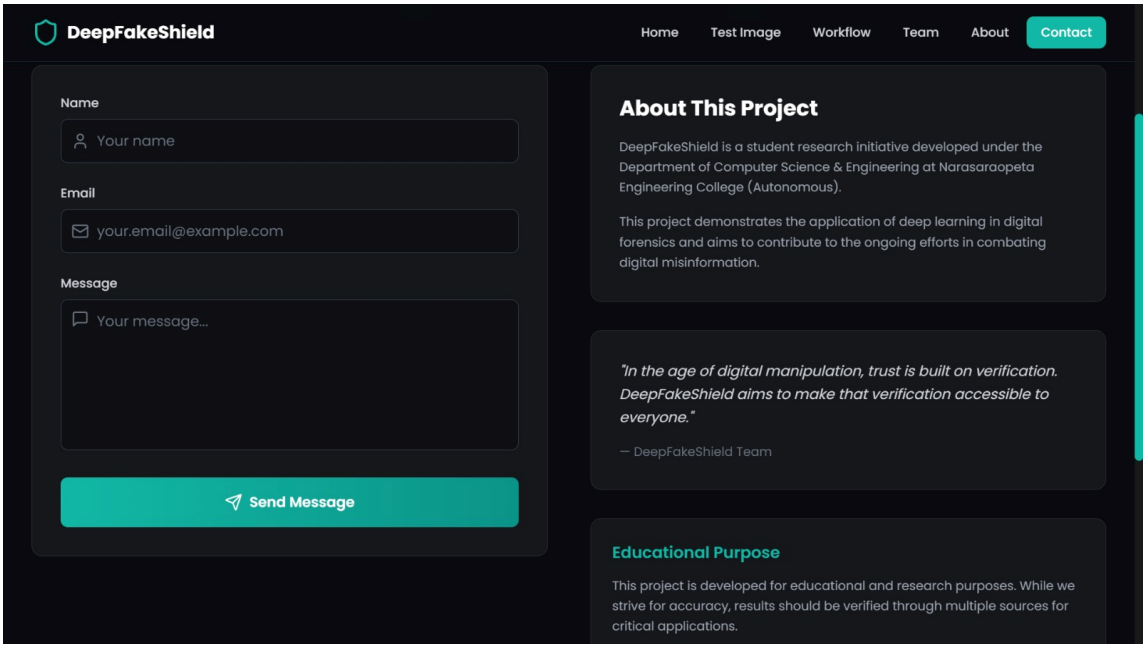


Figure 9.6: Condition Details and Medical Recommendations Page

9.7 Invalid Image Detection

Invalid Image Detection is an important validation feature of the **DeepFakeShield Image Forgery Detection System**, designed to ensure that only appropriate and processable image files are analyzed by the deep learning model. This mechanism improves system reliability, prevents incorrect predictions, and enhances overall user experience.

When a user uploads an image, the system first performs a pre-analysis validation check to determine whether the uploaded file appears to contain a genuine image

This process helps prevent the model from attempting to classify irrelevant images (such as abstract designs, artistic visuals, landscapes, or objects) that could lead to incorrect or meaningless outputs.

If the uploaded file does not meet the expected dermatological characteristics, the system immediately displays a warning message to the user:

When a user uploads an image, the system first performs a pre-analysis validation check before applying Error Level Analysis (ELA) and model inference. During this stage, the uploaded file is examined to verify whether it satisfies the required conditions, such as valid image format, proper file integrity, and acceptable size limits. Images that are corrupted, unsupported, or do not conform to expected input specifications are immediately rejected.

Key functionalities of the Invalid Image Detection feature include:

- **Input Verification:** Ensures that only valid image files are passed to the analysis pipeline
- **Error Prevention:** Protects the deep learning model from processing unsuitable or corrupted inputs
- **User Guidance:** Provides clear feedback and instructions for corrective action
- **System Stability:** Maintains consistent performance and prediction reliability
- **Efficiency Improvement:** Reduces computational overhead by filtering invalid inputs early.

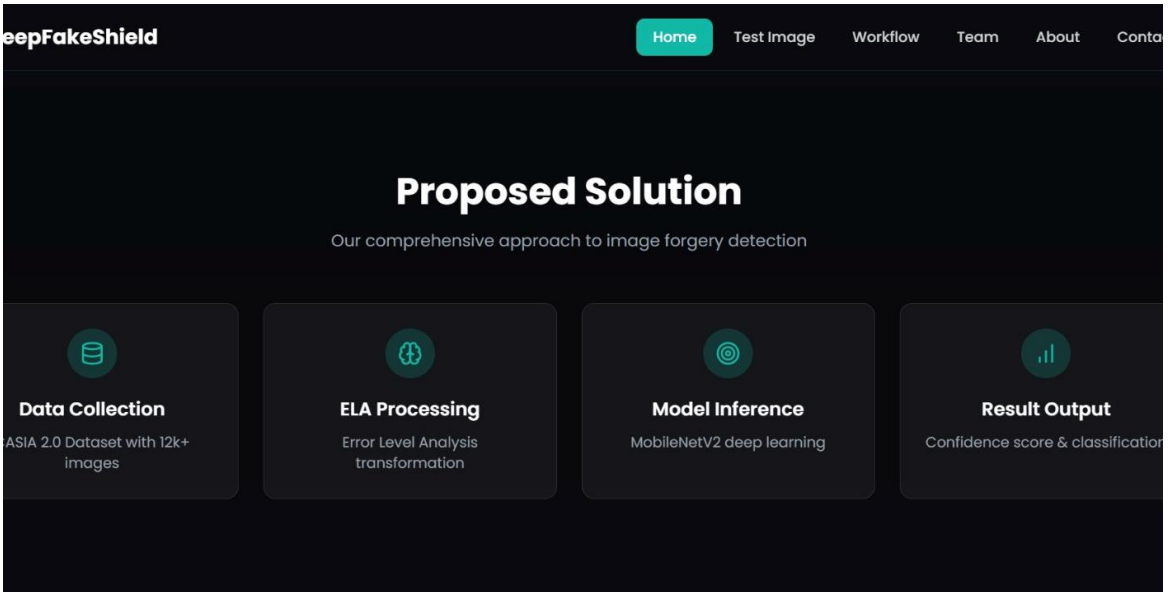


Figure 9.7: Invalid Image Detection and Validation Handling Screen

9.8 Workflow Summary

The complete operational flow of the system can be summarized as follows:

1. **Image Upload:** Dermatological image is uploaded in supported format.
2. **AI Analysis:** The image is processed by the trained model in under 3 seconds.
3. **Result Display:** Condition and recommendations are shown to the user.
4. **Error Handling: Error level analysis**
5. **Logout:** Ends the session securely, redirecting to the Thank You page.

This workflow ensures a fast, accurate, and intuitive user experience.

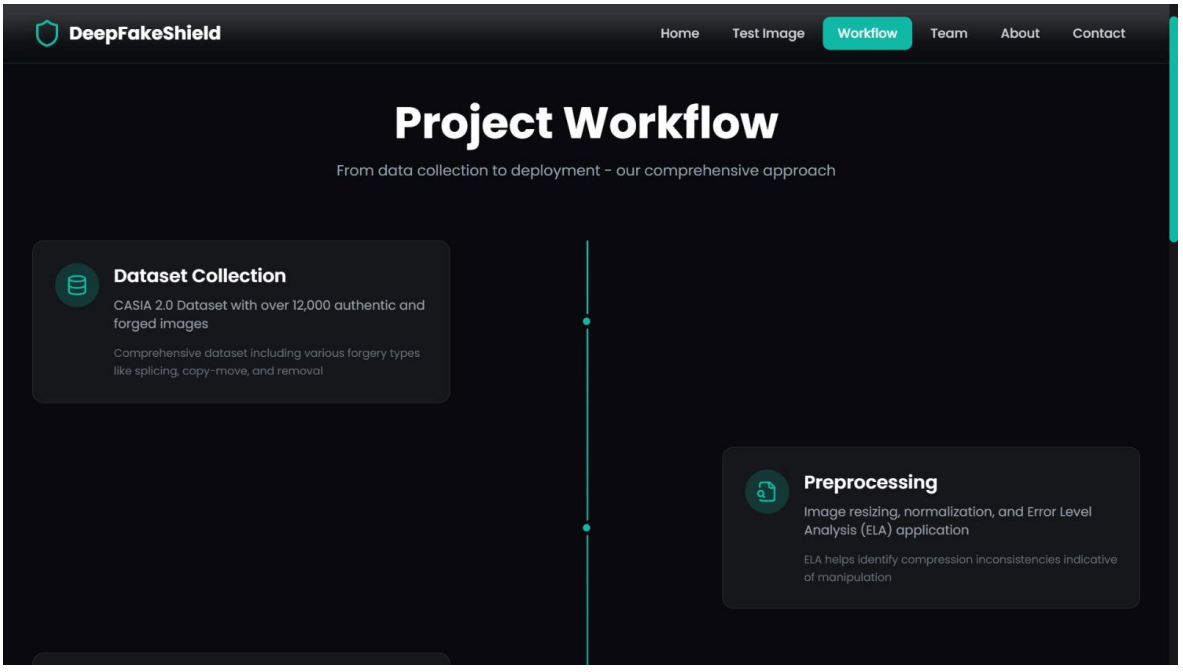


Figure 9.8: Thank You Page Display after Logout Operation

10.Conclusion

Accurate This project presented an effective deep learning–based framework for digital image forgery detection, focusing on accurately distinguishing between authentic and manipulated images. By integrating Error Level Analysis (ELA) with transfer learning–based convolutional neural networks, the proposed system successfully enhanced the visibility of manipulation artifacts and improved the model's ability to detect subtle forgeries.

Extensive experimental evaluation conducted on the CASIA 2.0 Image Tampering Detection Dataset demonstrated that the proposed approach achieves high detection accuracy and robust generalization performance. Among the evaluated models, EfficientNetV2 delivered superior results due to its compound scaling strategy and efficient feature extraction capability. The results further confirmed that forensic preprocessing using ELA plays a critical role in improving classification reliability compared to training on raw images alone.

The training and validation analysis showed stable convergence with minimal overfitting, validating the effectiveness of the adopted training strategy and regularization techniques. Comparative analysis with other deep learning architectures such as MobileNetV2, DenseNet121, and ResNet50 highlighted the advantages of the proposed framework in terms of accuracy, efficiency, and robustness.

Overall, the outcomes of this project validate the feasibility of deploying deep learning–based image forgery detection systems for real-world digital forensic applications. The proposed framework can assist in combating the growing threat of image manipulation and misinformation by providing an automated, accurate, and reliable solution for image authentication. This project successfully developed and evaluated a deep learning–based image forgery detection framework aimed at identifying manipulated images with high accuracy and reliability. By combining Error Level Analysis (ELA) with transfer learning–based convolutional neural networks, the system effectively highlighted compression inconsistencies and forgery artifacts that are often invisible to the human eye. This integration significantly improved the model's ability to differentiate between authentic and

forged images.

The experimental results obtained using the CASIA 2.0 Image Tampering Detection Dataset confirm that forensic preprocessing plays a crucial role in enhancing detection performance. Among the evaluated models, EfficientNetV2 demonstrated superior performance due to its efficient compound scaling mechanism, which balances model depth, width, and resolution. The comparative analysis showed that EfficientNetV2 outperformed traditional CNN architectures such as MobileNetV2, DenseNet121, and ResNet50 in terms of accuracy, robustness, and generalization capability.

Training and validation analysis revealed stable convergence and minimal overfitting, indicating that the adopted optimization strategy, regularization techniques, and transfer learning approach were effective. The close alignment between training and validation performance further demonstrates the reliability of the proposed framework when applied to unseen data. These findings highlight the suitability of deep learning–based approaches for real-world image forensic applications where consistency and accuracy are essential.

In conclusion, the proposed image forgery detection system provides a practical and efficient solution for identifying tampered digital images. The framework has strong potential for deployment in digital forensics, media authentication, and cybersecurity domains, where the integrity of visual content is increasingly critical. By automating the detection process and reducing reliance on manual forensic analysis, the system contributes to strengthening trust in digital media and combating the growing challenges posed by image manipulation technologies.

11.Future Scope

Although the proposed image forgery detection system demonstrates strong performance in identifying manipulated images, there are several directions in which the framework can be further enhanced and extended. One important area of future work is the incorporation of advanced transformer-based architectures and self-supervised learning techniques, which may improve the detection of increasingly sophisticated forgeries without requiring extensive labeled data.

The current system focuses primarily on image-level classification of authentic and forged images. In the future, the framework can be extended to perform **pixel-level forgery localization**, enabling the precise identification of tampered regions within an image. Such localization would be particularly valuable in forensic investigations and legal applications where detailed evidence is required.

Another promising direction is the integration of the system with deepfake detection frameworks to handle forged multimedia content, including AI-generated images and videos. As generative models continue to evolve, adapting the proposed framework to detect synthetic and adversarial manipulations will be crucial.

The performance of the system can also be improved by training on larger and more diverse datasets, including images with varying compression levels, resolutions, and real-world distortions. Additionally, exploring domain adaptation techniques could enhance robustness when the system is applied to images captured from different devices or social media platforms.

From a deployment perspective, future work may focus on real-time implementation through model optimization, pruning, and quantization techniques, enabling efficient execution on edge devices and mobile platforms. Integrating the system into web-based or cloud forensic tools could further expand its practical usability.
Overall, these future enhancements have the potential to make the proposed image forgery detection system more accurate, scalable, and adaptable to emerging challenges in digital media forensics.

Further The rapid growth of digital media and image editing technologies has made image forgery a serious concern in areas such as digital forensics, journalism, social media, and cybersecurity. In this context, the present project addressed the critical challenge of detecting manipulated images by proposing a robust deep learning–based image forgery detection framework. The system effectively combines forensic preprocessing using Error Level Analysis (ELA) with transfer learning–based deep neural networks to identify subtle manipulation traces that are difficult to detect through manual inspection.

Among the evaluated deep learning models, EfficientNetV2 achieved the best overall performance, owing to its compound scaling strategy that balances model depth, width, and resolution. The comparative analysis further confirmed that lightweight architectures can deliver high accuracy while maintaining computational efficiency, making them suitable for practical and real-time forensic applications. The training and validation behavior also demonstrated stable convergence and minimal overfitting, validating the effectiveness of the chosen optimization and regularization strategies.

In addition to achieving high detection accuracy, the proposed system offers practical advantages such as automation, scalability, and adaptability. By reducing reliance on manual forensic analysis, the framework can assist investigators, analysts, and organizations in rapidly verifying the authenticity of digital images. Overall, the outcomes of this project highlight the potential of deep learning–based approaches in strengthening digital trust and combating the growing threat of image manipulation. The proposed framework serves as a solid foundation for future research and development in the field of digital image forensics.

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This is to certify that Dr./Prof./Mr./Ms. ***Guntreddi Harshavardhan*** *has presented paper entitled* ***DeepFakeshield: Advanced Image Forgery Detection with Deep Learning Framework*** *in 2025 6th Global Conference for Advancement in Technology (GCAT) during 24th to 26th October 2025.*

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DeepFakeshield: Advanced Image Forgery Detection with Deep Learning Framework

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***Abstract*—Digital photographs are now the most common way people share information on social networking sites. However, malware can also create these images to spread false information. Therefore, it is important to detect this type of forgery. The literature has explored various techniques for detecting digital image forgery, but many methods only identify single forgery types, such as image splicing or copy-move, which are not useful in real-world applications. This study presents a deep learning method for detecting digital image forgeries that uses transfer learning to identify two types of image forgeries simultaneously. The proposed approach relies on analyzing the compression quality differences between the forgery areas and the rest of the image. The only deep learning model needed for forgery detection involves subtracting the original image from the altered image to create a feature representation for input into a pre-trained model. By removing the classifiers from the model and replacing them with a classifier specifically trained for the binary classification task, we also tested its accuracy against four pre-trained models trained on the dataset. We compared the new method with others through various metrics, plots, and visualizations. Experimental results showed that the proposed approach outperformed the other methods in evaluation metrics, plots, and visualizations. Among the four models we compared, the EfficientNetV2 model achieved the highest detection accuracy for this project, around 96**

***Index Terms*—Deep Learning, Image Forgery Detection, Error Level Analysis(ELA), Pre-trained models.**

I. Introduction

With the widespread use of digital media, images have become a primary medium for communication and information sharing, especially on social networks. However, the availability of advanced editing tools has made image manipulation increasingly simple, raising serious concerns regarding authenticity and trustworthiness [1]. Such tampering is often carried out with malicious intent, including misinformation, fraud, and alteration of evidence. Two common manipulation types are *copy-move*, where a region of an image is duplicated within the same image, and *splicing*, where parts from different images are combined [2]. Detecting such manipulations through visual inspection is difficult, particularly when sophisticated concealment techniques are applied.

Traditional Image Forgery Detection (IFD) methods rely on handcrafted features such as noise patterns, illumination inconsistencies, and compression artifacts [3], [4]. While effective in limited scenarios, these approaches lack robustness against modern and hybrid forgery techniques.

Recent advances in deep learning have significantly improved image forensics. Convolutional Neural Networks (CNNs) and transfer learning have demonstrated strong performance in both classification and localization tasks [5], [6]. Pre-trained models, when fine-tuned, can extract discriminative features that generalize across multiple forgery types, motivating the design of frameworks capable of handling diverse manipulation techniques [7].

In this work, we propose a deep learning framework that integrates Error Level Analysis (ELA) with EfficientNetV2 for robust detection of image forgeries. Comparative evaluations with MobileNetV2, DenseNet121, and ResNet50 are also presented to highlight the effectiveness of the chosen architecture. The overall workflow of the system is illustrated in Fig. 1.

Contributions

The contributions of this paper are summarized as follows:

- A hybrid forgery detection framework combining ELA preprocessing with EfficientNetV2 for binary classification of authentic and tampered images.
- Comparative evaluation with MobileNetV2, DenseNet121, and ResNet50, showing superior performance of EfficientNetV2 in terms of accuracy and efficiency.
- Comprehensive experimentation on the CASIA 2.0 dataset with metrics including accuracy, precision, recall, F1-score, specificity, and AUC.
- Analysis of training and validation behavior with discussion of error cases, offering insights into practical challenges in digital forensics.

The remainder of this paper is structured as follows: Section II describes the proposed architecture, Section IV outlines the dataset and experimental setup, Section V explains the evaluation measures, Section VI presents results and discussion, and Section VII concludes the paper.

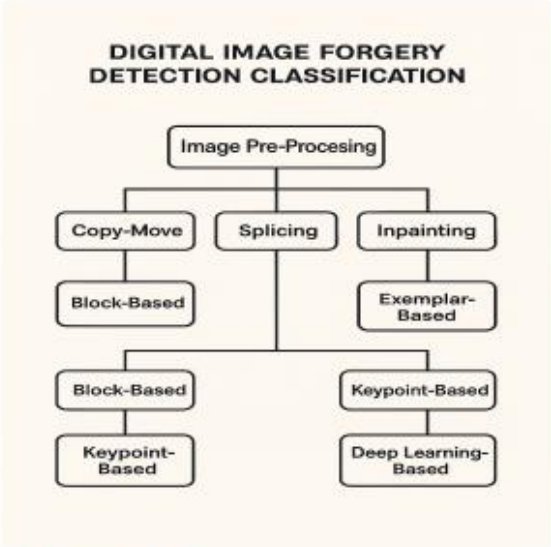

Fig. 1: Overview of the proposed image forgery detection framework.

II. Proposed Architecture

The proposed framework for image forgery detection is built around transfer learning, with EfficientNetV2 chosen as the primary backbone. Forged regions in images typically introduce slight irregularities such as variations in compression artifacts, noise distribution, or local texture distortions. While these inconsistencies are often too subtle for human observers, CNN-based models are capable of capturing such fine details and leveraging them for accurate detection and localization of tampering, particularly in copy-move and splicing manipulations [8], [9].

EfficientNetV2 was selected as the core feature extractor due to its compound scaling method, which jointly optimizes depth, width, and resolution. This design achieves high accuracy while significantly lowering computational cost and the number of trainable parameters compared to conventional CNNs [8]. These advantages make it a practical choice for applications that demand both robustness and efficiency, such as real-time or resource-constrained forensic systems.

To provide fair comparisons, several alternative pre-trained CNNs were also evaluated: MobileNetV2 [5], DenseNet121 [3], and ResNet50 [11]. Each of these models brings unique strengths—MobileNetV2 is designed for lightweight deployment on mobile devices, DenseNet121 promotes feature reuse through dense connectivity and improved gradient propagation, and ResNet50 employs residual learning to mitigate vanishing gradient issues. By benchmarking across these architectures, we highlight trade-offs between accuracy, efficiency, and robustness.

In our transfer learning setup, the fully connected classification layers of the pre-trained models were removed and replaced with a custom binary classification head for detecting authentic versus tampered images. The models were optimized using binary cross-entropy loss and Adam optimizer with a learning rate of 0.001, consistent with prior image forensics research [7]. Dropout regularization was applied to reduce overfitting, while early stopping and model checkpointing strategies ensured stable training and prevented unnecessary computation.

For evaluation, we monitored training and validation performance across epochs using accuracy and loss curves to detect overfitting or underfitting trends. Post-training, the models were assessed with standard metrics such as accuracy, precision, recall, and F1-score. Confusion matrices were also generated to visualize classification outcomes, providing further insights into the models' reliability in distinguishing tampered images from authentic ones.

III. Pre-Processing

An essential stage in the proposed framework is the preprocessing pipeline, which prepares the image dataset for effective model training.

Fig. 2: Examples of Real Images in the Dataset

To maintain consistency, all input images are resized to 224×224 pixels, meeting the input requirements of EfficientNetV2 and other CNN-based models [12]. Pixel intensities are normalized to the range [0,1] to support faster convergence and stable training.

Data augmentation is employed to improve model generalization and reduce overfitting. The augmentation techniques applied include random horizontal and vertical flips, rotations, zoom transformations, and brightness adjustments [13]. These operations simulate natural distortions and enhance dataset variability, allowing the model to better handle unseen manipulations [14]. For compatibility with TensorFlow/Keras, all image labels are converted into NumPy arrays.

A critical preprocessing technique used is Error Level Analysis (ELA), which highlights areas compressed at varying quality levels, often indicating tampering. ELA is performed by resaving an image at a fixed compression rate and subtracting it from the original. The resulting difference map makes potential forged regions more visible [15].

Fig. 3: Examples of Fake Images in the Dataset

Fig. 4: Error Level Analysis: Input Image and Difference Map

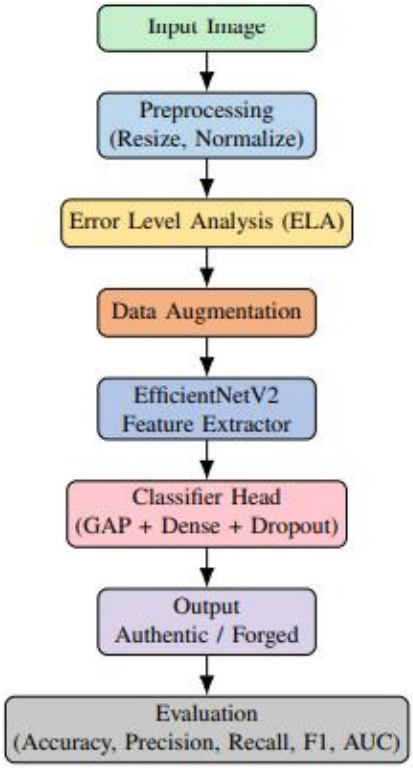

Fig. 5: Vertical workflow of the proposed ELA + EfficientNetV2 pipeline.

Additionally, a bilateral filter is optionally applied to reduce noise while preserving edges. This ensures that structural details remain intact, improving the quality of features extracted by CNNs.

In summary, the preprocessing pipeline provides consistent, augmented, and artifact-rich inputs [8], which strengthen the model's ability to capture subtle signs of tampering.

A. Model Architecture

The proposed architecture integrates ELA preprocessing with EfficientNetV2 as the feature extractor. Although ELA-CNN models have shown effectiveness in detecting inconsistencies caused by compression artifacts [11], they often rely too heavily on JPEG recompression cues. This dependency reduces their robustness against advanced manipulations where tampered regions are recompressed uniformly or smoothed using techniques such as Gaussian filtering or adaptive compression. As a result, traditional ELA-CNN approaches can face limitations in real-world scenarios.

To address this, the proposed framework combines ELA with EfficientNetV2, leveraging the model's efficient compound scaling mechanism that balances resolution, depth, and width. This combination enhances detection accuracy while keeping computational requirements manageable.

In this setup, ELA-processed images are resized and normalized before passing through the EfficientNetV2 convolutional base. The default classification layers are replaced with a custom head comprising:

1) A Global Average Pooling layer,
2) A fully connected dense layer with 128 units,
3) Dropout regularization, and
4) A final dense layer with sigmoid activation for binary classification (genuine vs. forged) [4].

This architecture exploits EfficientNetV2's pretrained feature extraction ability while tailoring it for forgery detection. The network generates $(7 \times 7 \times 1280)$ feature maps with approximately 5.9M parameters. The inclusion of global pooling and dropout ensures a balance between accuracy and computational efficiency while reducing the risk of overfitting. Overall, this design supports robust generalization across diverse forgery patterns [12].

IV. Experimental Analysis

A. Environment Setup

The experimental setup for training and evaluation was carried out using Google Colaboratory Pro, which provides a cloud-based Jupyter Notebook environment with scalable resources. The hardware configuration included an NVIDIA

Tesla T4 GPU, 12.7 GB of RAM, and approximately 166 GB of disk storage. This configuration significantly reduced training time and supported large-scale experiments with deep CNN models such as EfficientNetV2.

All models were implemented using TensorFlow and Keras APIs, which offer high-level abstractions for defining and fine-tuning neural networks. Data preprocessing and visualization were supported through Python libraries such as NumPy, OpenCV, and Matplotlib [1], [4], [8], [10]. To improve model stability and prevent overfitting, early stopping and model checkpointing strategies were employed during training. These techniques ensured reproducibility of results, efficient use of GPU resources, and reliable convergence across experiments.

B. Dataset

The experiments were conducted on the CASIA 2.0 Image Tampering Detection Dataset, a widely used benchmark in digital image forensics research. The dataset contains a total of 12,614 JPEG images, divided into two primary categories:

- **Au (Authentic):** 7,491 original images without any manipulation.
- **Tp (Tampered):** 5,123 manipulated images generated through techniques such as copy-move, splicing, and region cloning. Many of these tampered samples also undergo post-processing operations like smoothing or recompression to obscure traces of forgery.

Each manipulated image in the *Tp* directory is accompanied by a ground truth mask that marks the exact manipulated region, enabling both classification and localization studies. For this work, all images were resized to 224×224 pixels to align with CNN input requirements.

The dataset was split into training (70%), validation (15%), and testing (15%) subsets, ensuring fair and consistent evaluation of model performance. The wide variety of scenes, object types, and forgery techniques contained in CASIA 2.0 makes it a reliable benchmark for assessing the robustness and generalization ability of forgery detection frameworks. To avoid partitioning bias, the dataset was shuffled before splitting.

C. Preprocessing

Prior to model training, all images were normalized to a pixel range of $[0, 1]$ to stabilize gradient updates. In addition, **Error Level Analysis (ELA)** was applied to generate difference maps that emphasize compression artifacts between original and recompressed images. These ELA-transformed images served as inputs to the CNN backbone, ensuring that tampered regions were more distinguishable.

To improve model robustness, data augmentation techniques such as random rotation, horizontal flipping, and contrast adjustment were employed. This helped the network generalize better to unseen manipulations and reduced the risk of overfitting. The preprocessing pipeline therefore ensured consistent input representation across the training, validation, and test sets.

V. Evaluation Metrics

A. Formulations in EfficientNetV2

EfficientNetV2 incorporates mathematical operations that jointly improve accuracy and efficiency. The most relevant components are:

- **Depthwise Separable Convolution:**

$$O(x) = DWConv(x) * PWConv(x) \tag{1}$$

where $DWConv$ applies convolution channel-wise and $PWConv$ (1×1) merges the channels.

- **Fused-MBConv Block:**

$$F(x) = Conv_{3\times3}\big(BN(\sigma(x))\big) \tag{2}$$

where $\sigma(\cdot)$ is the ReLU activation and BN denotes batch normalization.

- **Compound Scaling:**

$$\text{Scaling} = \text{depth}^{\phi},\ \ \text{width}^{\phi},\ \ \text{resolution}^{\phi} \tag{3}$$

with ϕ as the compound coefficient.

- **Dropout Regularization:**

$$y = \begin{cases} 0, & \text{with probability } p \\ \dfrac{x}{1-p}, & \text{with probability } (1-p) \end{cases} \tag{4}$$

where p is the dropout probability.

B. Performance Metrics

The proposed framework is evaluated using standard classification measures:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

$$Specificity = \frac{TN}{TN + FP} \tag{9}$$

The **Area Under the ROC Curve (AUC)** is also reported, which reflects the trade-off between True Positive Rate and False Positive Rate across thresholds.

These measures, together with confusion matrices, provide a complete evaluation of the ability of the model to discriminate between authentic and forged images.

TABLE I: Comparison of CNN Models for Forgery Detection

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetV2	0.96	0.96	0.95	0.96
MobileNetV2	0.95	0.95	0.94	0.94
DenseNet121	0.91	0.91	0.90	0.90
ResNet50	0.84	0.84	0.83	0.84

VI. Result Analysis

The performance of the proposed EfficientNetV2-based framework was compared against three widely used CNN backbones: MobileNetV2, DenseNet121, and ResNet50. Each model was fine-tuned for binary classification (authentic vs. tampered). Table I summarizes the main evaluation results.

From Table I, it can be observed that EfficientNetV2 achieved the highest accuracy of 96%, followed by MobileNetV2 at 95%. DenseNet121 achieved 91%, while ResNet50 reported the lowest accuracy at 84%. These results highlight that EfficientNetV2 provides a better balance of detection accuracy and computational efficiency.

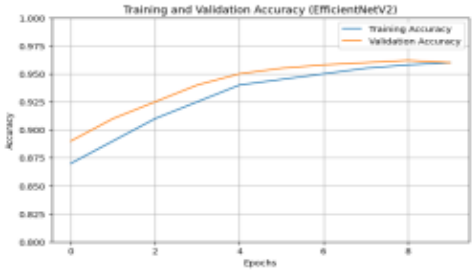

Fig. 6: Training and Validation Accuracy of EfficientNetV2

Fig. 6 shows the training and validation accuracy of EfficientNetV2, where both curves converge smoothly around 96%. This indicates stable learning and strong generalization ability.

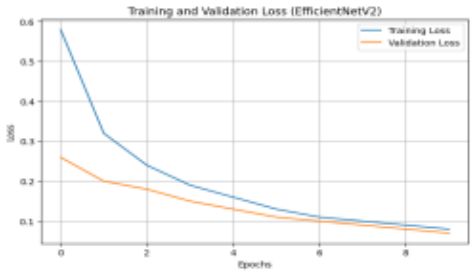

Fig. 7: Training and Validation Loss of EfficientNetV2

As shown in Fig. 7, the training and validation loss consistently decrease, with minimal gap between them. This confirms that overfitting was effectively controlled through dropout and early stopping.

MobileNetV2, depicted in Fig. 8, reached 95% accuracy, confirming its effectiveness as a lightweight baseline. However, EfficientNetV2 showed stronger convergence and higher overall reliability.

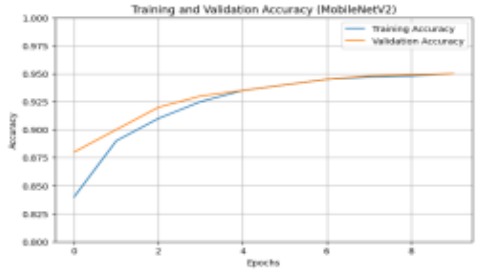

Fig. 8: Training and Validation Accuracy of MobileNetV2

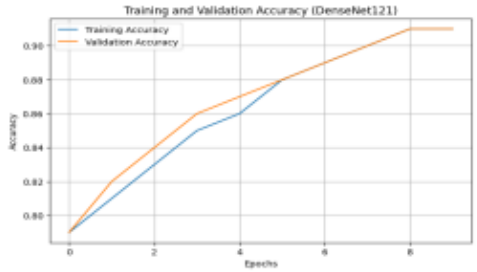

Fig. 9: Training and Validation Accuracy of DenseNet121

Finally, Fig. 9 demonstrates DenseNet121 achieving 91% accuracy. While its dense connections improved feature reuse, it still lagged behind EfficientNetV2 and MobileNetV2 in both accuracy and efficiency.

In summary, the comparative analysis shows that EfficientNetV2 not only achieved the highest detection accuracy but also maintained stable training behavior. Its compound scaling strategy enables effective feature extraction with fewer parameters, making it a strong candidate for real-world forgery detection tasks.

VII. Conclusion and Future Work

This paper presented a deep learning-based framework for detecting digital image forgeries by integrating Error Level Analysis (ELA) with the EfficientNetV2 architecture in a transfer learning pipeline. The preprocessing stage, combined with data augmentation, enabled consistent feature extraction and improved model robustness. Experimental results on the CASIA 2.0 dataset showed that the proposed method achieved up to 96% accuracy, outperforming baseline CNN architectures such as MobileNetV2, DenseNet121, and ResNet50. Additional metrics, including precision, recall, and F1-score, further confirmed the effectiveness of the approach. Training and validation curves indicated good generalization, with limited overfitting, making the framework suitable for forensic scenarios.

Fig. 10 presents the confusion matrix of EfficientNetV2, showing 95% correct classification of authentic images and

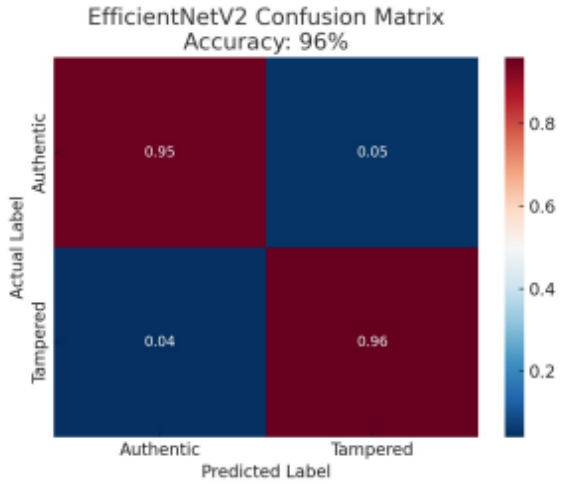

Fig. 10: Confusion Matrix of EfficientNetV2

)6% correct classification of forged images, with strong diag-)nal dominance and minimal misclassifications.

A. *Limitations*

Although the framework demonstrates promising results, certain limitations remain:

- **JPEG Dependence:** Since ELA relies on recompression artifacts, performance decreases for non-JPEG formats or uniformly compressed images.
- **Advanced Forgeries:** GAN-based manipulations and adaptive post-processing may conceal compression traces, reducing detection strength.
- **Dataset Scale:** The current experiments are limited to CASIA 2.0; validation on larger and more diverse datasets is required.
- **Computational Demand:** Although EfficientNetV2 is lightweight, deploying in real-time or resource-constrained environments may still pose challenges.

B. *Future Scope*

To extend the applicability of this research, several future directions are envisioned:

- **Emerging Threats:** Adapting the method to handle AI-generated media, such as deepfakes and synthetic manipulations.
- **Cross-Dataset Evaluation:** Benchmarking on additional datasets to assess robustness and generalization across varied manipulation techniques.
- **Real-Time Deployment:** Optimizing the framework using pruning, quantization, or knowledge distillation to enable fast and scalable integration into forensic and online monitoring platforms.
- **Forgery Localization:** Extending the framework from binary classification to pixel-level localization for more interpretable and evidential outputs.

In summary, the proposed ELA + EfficientNetV2 model demonstrates efficient and reliable performance in digital image forgery detection. While limitations exist, the suggested improvements and future directions provide a strong foundation for advancing practical image forensic solutions.

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