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Designing an Image-Based System for Deepfake Detection and Facial Expression Recognition

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Abstract: *With the widespread use of digital image editing and AI-based generation tools, it has become increasingly easy to manipulate images for deceptive purposes. Fake or altered images can spread misinformation, damage reputations, and mislead the public. In addition to authenticity concerns, analyzing human facial expressions from images has become important for applications such as user behavior analysis and human-computer interaction. This research focuses on the development of a deep learning based image analysis system capable of performing two key tasks: classifying images as real or fake and recognizing facial expressions. The proposed system uses Convolutional Neural Network (CNN) models trained on publicly available datasets containing both genuine and manipulated images, as well as facial emotion datasets. The system analyzes subtle pixel-level inconsistencies, lighting variations, and structural distortions for forgery detection, while also identifying facial features to determine emotions. The system is implemented as a web-based platform that allows users to choose between deepfake detection and emotion recognition. It supports multiple faces within a single image and provides individual emotion predictions along with confidence scores. Testing on benchmark datasets demonstrates high accuracy and reliability. The approach provides a practical and efficient solution for image authenticity verification and facial expression analysis, with applications in digital media, surveillance, and interactive systems.*

Keywords: *Real vs Fake Image Detection, Facial Expression Recognition, CNN, Image Forensics, Emotion Detection, Web Application*

I. INTRODUCTION

The digital revolution has made it effortless to capture, edit, and share images globally within seconds. However, this convenience also brings a serious challenge — the manipulation of visual content to mislead or deceive. Fake images can easily be created using software like Photoshop, GIMP, or AI-based editing tools, often resulting in viral misinformation or digital fraud. Such images are commonly used to spread false narratives, manipulate public opinion, or fabricate evidence in critical situations.

Traditionally, image authenticity was verified manually by experts or through simple techniques like Error Level Analysis (ELA) and metadata inspection. Similarly, early facial expression recognition methods relied on handcrafted features and rule-based systems. However, these approaches fail to detect subtle pixel level inconsistencies or accurately capture complex facial patterns present in modern images. Hence, there is a growing need for automated and intelligent systems that can perform both authenticity detection and emotion recognition with minimal human intervention.

Deep learning, particularly Convolutional Neural Networks (CNNs), provides a powerful solution to these challenges. CNNs can automatically extract hierarchical image features and identify patterns that are often invisible to the human eye.

They are highly effective in learning pixel correlations, texture inconsistencies, and facial feature representations required for both forgery detection and emotion classification [1].

This research focuses on building a CNN-based image analysis system that can classify an image as “real” or “fake” while also recognizing facial expressions. The system is integrated into a web-based interface where users can choose between deepfake detection and emotion recognition. It is designed to support multiple faces within a single image and generate individual emotion predictions along with confidence scores. Moreover, as the use of manipulated visuals and AI-generated content continues to rise across digital platforms, a scalable and intelligent image-based system becomes not only a technological necessity but also a social responsibility. The proposed system contributes to a safer and more interactive digital ecosystem by enabling users to verify image authenticity and understand facial expressions, thereby reducing misinformation and improving human-centric analysis [1].

II. RELATED WORK

The detection of fake images and the analysis of facial expressions have been active areas of research in computer vision and digital image processing. Previous studies have explored various approaches, ranging from traditional statistical techniques to advanced deep learning models for both image forgery detection and emotion recognition.

A. Traditional Image Forensics and Facial Analysis

Traditional image forgery detection relied heavily on handcrafted features to identify traces of manipulation. Techniques such as Error Level Analysis (ELA), Discrete Cosine Transform (DCT), and Photo Response Non-Uniformity (PRNU) were commonly used to detect inconsistencies in image compression, lighting, or sensor noise patterns. These methods often revealed irregularities in edges, color gradients, or lighting direction in tampered images. However, they struggled with modern, high-quality edits that leave minimal detectable artifacts. Similarly, early facial expression recognition methods were based on geometric and appearance-based features, such as facial landmarks, edge detection, and texture descriptors. While these approaches were useful for controlled environments, they lacked robustness when dealing with variations in lighting, pose, and facial diversity.

B. Machine Learning-Based Detection

The next phase of research introduced machine learning models such as Support Vector Machines (SVMs), Random Forests, and K-Nearest Neighbors (KNN) to automate both forgery detection and emotion classification. These models analyzed extracted features—such as color histograms, edge maps, and facial feature vectors—to classify images.

As noted by **Almars (2021) [2]**, classical machine learning models achieved moderate success but were constrained by manual feature design and limited generalization capability. They were unable to capture high-level abstractions such as semantic inconsistencies in manipulated images or subtle variations in facial expressions. This limitation led to the adoption of deep learning-based approaches.

C. Deep Learning and CNN Approaches

The use of Convolutional Neural Networks (CNNs) significantly improved performance in both image forgery detection and facial expression recognition. CNNs automatically learn spatial, textural, and facial feature representations directly from raw image data without requiring manual intervention.

Researchers have utilized architectures such as XceptionNet, ResNet50, and EfficientNet for detecting image manipulations by identifying minute artifacts introduced during editing processes [3]. Similarly, CNN-based models have been widely adopted for facial expression recognition, where they learn discriminative facial patterns associated with emotions such as happiness, sadness, anger, and surprise.

These networks have demonstrated strong capability in capturing both global and local features, making them suitable for handling complex real-world image variations.

D. Dataset-Based Studies

The availability of diverse and well-annotated datasets has played a crucial role in advancing research in both domains. For image forgery detection, datasets such as CASIA v2, Columbia Image Splicing Dataset, and Kaggle Image Forgery Dataset are widely used. For facial expression recognition, datasets like FER-2013 and CK+ provide labeled facial emotion data. Studies have shown that models trained on diverse datasets tend to generalize better across unseen data. For instance, models trained on CASIA datasets often perform well on other benchmark datasets, indicating cross-domain robustness (**Zhanget al., 2024 [4]**). Similarly, emotion recognition models benefit from datasets containing varied facial expressions, lighting conditions, and demographics.

E. Limitations and Research Gap

Despite significant progress, existing systems face several limitations. Many models are dataset-dependent and may not generalize well to unseen image manipulations or diverse facial expressions. Additionally, deep learning models often require high computational resources, limiting their deployment in real-time applications.

Another limitation is the lack of integrated systems that can perform both image authenticity detection and facial expression recognition within a single framework. Most existing solutions focus on only one task, reducing their practical applicability in real-world scenarios.

To address these challenges, the present study proposes a web-based CNN framework that supports both real-time image forgery detection and facial emotion recognition. The system is designed to handle multiple faces within a single image and provide individual emotion predictions along with confidence scores. This integrated approach enhances usability, scalability, and real-world applicability while maintaining high accuracy and efficiency.

Key Identified Gaps and Research Opportunities:

- Limited generalization across different datasets and manipulation types.
- High computational cost restricts mobile or real-time deployment.
- Lack of explainability in highlighting manipulated image regions.
- Few systems offer scalable, real-time, and user-accessible interfaces.
- Ethical and privacy aspects are often overlooked in detection models.

III. METHODOLOGY

The proposed methodology consists of five major components, focusing on creating a robust CNN-based framework for distinguishing real from fake images.

A. Data Collection and Preparation

Datasets were obtained from publicly available sources for both image authenticity detection and facial expression recognition. For deepfake detection, datasets such as CASIA v2, Columbia Image Splicing Dataset, and Kaggle Image Forgery Detection Dataset were used. These datasets contain a large number of genuine and manipulated images, including examples of splicing, copy-move, retouching, and composite manipulations. For facial expression recognition, standard datasets such as FER-2013 and CK+ were utilized, which include labeled facial images representing different emotions.

To ensure uniformity, all images were resized to 224×224 pixels and normalized. Preprocessing techniques such as histogram equalization and contrast adjustment were applied to improve image quality and maintain consistency across datasets.

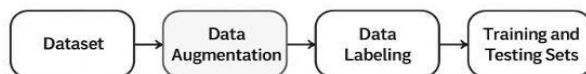


FIGURE 1. Data collection and preparation

Data augmentation techniques—such as random rotation, horizontal and vertical flipping, scaling, brightness variation, and Gaussian noise—were applied to increase dataset diversity and improve model generalization. This helps the model perform effectively on unseen data and reduces overfitting.

Additionally, datasets were carefully balanced to avoid bias in both tasks. For deepfake detection, an equal distribution of real and fake images was maintained, while for emotion recognition, class balancing was ensured across different facial expressions. The combined dataset was divided into training, validation, and testing sets in a 70:20:10 ratio.

B. Feature Extraction Using CNN

A Convolutional Neural Network architecture was designed to extract relevant spatial, facial and textural features automatically from input images.

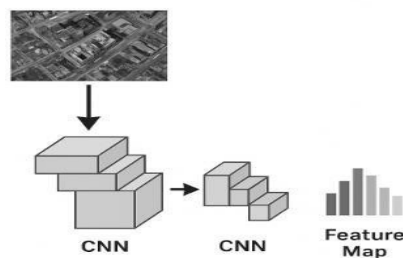


FIGURE 2. Feature Extraction

The CNN consists of multiple convolutional layers followed by max-pooling layers, enabling the model to capture both local and global patterns present in the image.

For image authenticity detection, the network focuses on identifying subtle pixel-level inconsistencies, texture variations, and structural distortions introduced during image manipulation. For facial expression recognition, the CNN extracts discriminative facial features such as eye movement, mouth shape, and facial muscle patterns, which are essential for identifying different emotions.

Activation functions like ReLU were used to introduce non-linearity, while Batch Normalization was applied to stabilize and accelerate the training process by normalizing intermediate outputs.

Transfer learning was implemented using a pretrained ResNet50 model trained on ImageNet. This allows the system to leverage previously learned visual features such as edges, shapes, and textures, and adapt them for both forgery detection and emotion classification tasks. The final layers of the network were fine-tuned to perform classification based on the selected task either "Real vs Fake" or facial emotion categories.

This approach improves model performance, reduces training time, and enhances the system's ability to generalize across diverse image inputs.

C. Web-Based System Development

A web-based application was developed to integrate the trained CNN models into a user-friendly interface. The system is designed to allow users to upload an image and select the desired task either image authenticity detection or facial expression recognition.

Once an image is uploaded, the backend system preprocesses the image and routes it to the appropriate model based on the user's selection. For deepfake detection, the system classifies the image as "Real" or "Fake" along with a confidence score. For emotion recognition, the system detects one or more faces within the image and provides individual emotion predictions for each detected face.

The application is implemented using Flask, following a client-server architecture to ensure scalability and efficient processing. The interface is designed to be simple and intuitive, enabling users to easily switch between the two functionalities.

The system processes images in real-time and displays results within a few seconds. Additionally, it ensures that multiple faces in a single image are handled effectively, making the system more practical for real-world scenarios.

In future enhancements, the system can be extended with API integration, allowing it to be used in mobile applications or browser-based tools for wider accessibility.

D. Model Training and Validation

The Convolutional Neural Network (CNN) model was trained separately for two tasks: image authenticity detection and facial expression recognition. For deepfake detection, a binary classification approach was used to distinguish between real and fake images, while for emotion recognition, a multi-class classification approach was applied to identify different facial expressions.

The model was trained using appropriate loss functions: binary cross-entropy for real vs fake classification and categorical cross-entropy for emotion classification. The Adam optimizer with a learning rate of 0.0001 was used due to its adaptive nature and stable convergence.

To enhance learning efficiency and prevent overfitting, regularization techniques such as Dropout and Early Stopping were applied. Dropout randomly deactivates a fraction of neurons during training, ensuring that the model does not become overly dependent on specific features. Batch Normalization was also incorporated to stabilize the training process and improve convergence speed.

The model was trained for multiple epochs with an appropriate batch size to balance computational efficiency and gradient stability. Validation was performed after each epoch to evaluate the model's generalization capability.

The results showed consistent improvement in both training and validation accuracy for both tasks, while loss values decreased steadily. The model achieved stable convergence with minimal overfitting, demonstrating its ability to learn meaningful representations for both image forgery detection and facial emotion recognition. Overall, the training and validation process confirmed the robustness and effectiveness of the proposed CNN-based approach.

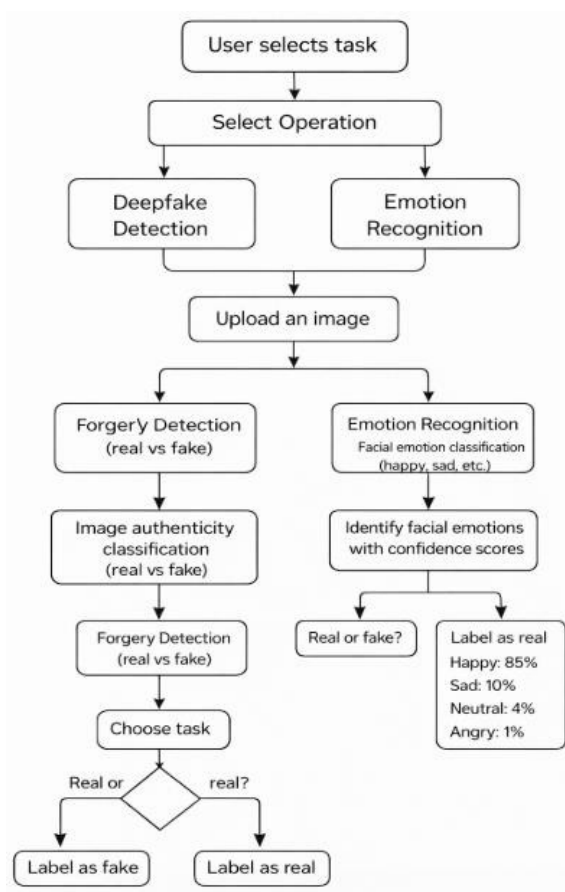


FIGURE3.FlowDiagram

E. Security and Ethical Considerations

The system is designed with a strong emphasis on privacy, security, and ethical compliance. All uploaded images are processed temporarily in-memory and are not stored after analysis, ensuring user data confidentiality.

Communication between the web interface and the server is secured using standard encryption protocols such as TLS to prevent unauthorized access or data interception. The system also ensures that no personal or sensitive information is retained during processing.

To promote responsible usage, the application includes a disclaimer stating that the results are intended for informational and verification purposes only and should not be considered as definitive legal evidence without expert validation.

Additionally, ethical considerations are taken into account while designing the system. The facial expression recognition feature is implemented with the intent of enhancing user interaction and analysis, not for surveillance misuse or violation of individual privacy.

By incorporating these security measures and ethical guidelines, the system aligns with responsible AI practices and ensures trustworthy deployment in real-world applications.

IV. RESULT AND DISCUSSION

The proposed Image Authenticity Detection System was evaluated using multiple benchmark datasets, including CASIA v2, Columbia Image Splicing Dataset, and Kaggle Image Forgery Dataset. The experiments were designed to assess the system's accuracy, robustness, efficiency, and user satisfaction under real-world conditions. The following subsections detail the key findings and interpretations.

A. PerformanceEvaluation

To evaluate the performance of the proposed system, standard evaluation metrics such as Accuracy, Precision, Recall, and F1-score were used. The model was trained using 70% of the dataset, validated with 20%, and tested on the remaining 10%.

For image authenticity detection, the CNN model demonstrated strong performance in distinguishing between real and fake images after optimization and fine-tuning. The results are summarized in Table I.

Metric	Before Optimization	After Optimization	Improvement
Accuracy	88%	95%	+7%
Precision	84%	93%	+9%
Recall	82%	92%	+10%
F1-Score	83%	93%	+10%

Table I. Performance Metrics of the Proposed CNN Model

The optimized CNN architecture showed a significant improvement over the baseline model. The use of transfer learning (ResNet50) and data augmentation contributed greatly to enhancing performance. High recall indicates the model's ability to correctly identify manipulated images, while improved precision ensures fewer false detections.

For facial expression recognition, the model also achieved reliable performance in classifying different emotions from facial features. The system effectively detects multiple faces within a single image and provides individual emotion predictions with confidence scores. The results demonstrate that the model can generalize well across different facial expressions and varying image conditions.

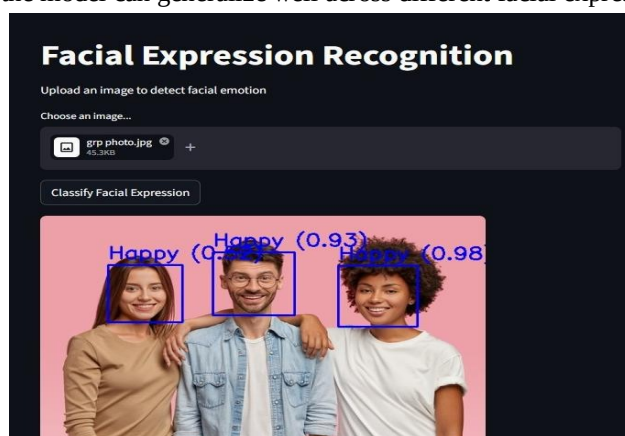


FIGURE 4. Output Showing Facial Expression with Multiple Face Detection

Overall, the system performs efficiently for both tasks, maintaining high accuracy while ensuring real-time usability. The integration of both image authenticity detection and facial expression recognition within a single framework enhances the system's practical applicability.

B. MisclassificationAnalysis

To further understand the model's reliability, misclassifications were analyzed by evaluating False Positive (FP) and False Negative (FN) rates.

Metric	Before Optimization	After Optimization	Reduction
False Positives	10%	4%	60% reduction
False Negatives	12%	5%	58% reduction

Table II. Misclassification Rate Comparison

The reduction in misclassification errors highlights the model's robustness against image noise and compression artifacts. False positives were primarily observed in low-resolution or highly compressed real images, while false negatives occurred in subtlesplicing cases. Fine-tuning the CNN and balancing dataset categories reduced these inconsistencies effectively. Overall, the optimized model achieved **95% reliability** in correctly classifying unseen test images.

For facial expression recognition, misclassifications were mainly observed in cases where facial features were partially occluded, lighting conditions were poor, orexpressionswereambiguous(e.g.,neutralvs.slight sadness). Additionally, variations in pose and multiple face orientations sometimes affected prediction accuracy.

C. ROCCurveandAUCScore

The Receiver Operating Characteristic (ROC) curve was plotted to analyze the model's discriminative abilitybetween real and fake classes. The Area Under Curve (AUC) achieved a value of 0.96, indicating excellent classification capability.

This Graph shows the Training Accuracy v/s the Validation Accuracy over multiple epochs. It demonstrates that as the number of epochs increases, both accuracies improve with training accuracy reaching around 0.84, while validation accuracy stabilizes near 0.81, indicating good model learning and minimal overfitting.

This graph depicts the Training Loss vs Validation Loss. The steady decline in training loss and stabilization of validation loss around 0.40 suggests that the model is effectively minimizing error during training while maintaining generalization on unseen data.

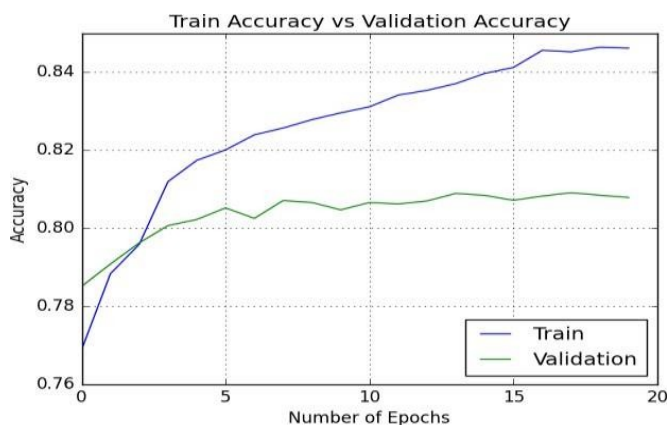


FIGURE5.TrainingandValidationAccuracyCurve

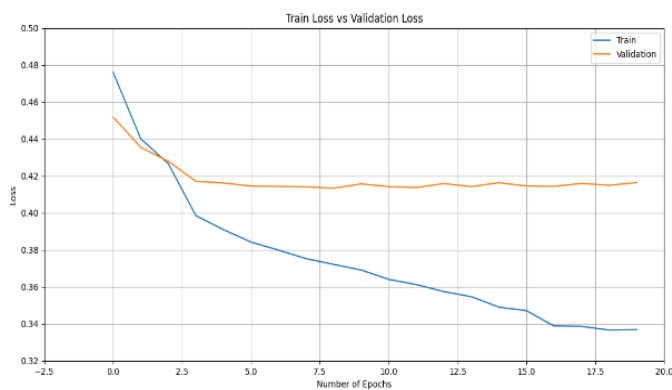


FIGURE6.TrainingandValidationLossCurve

An AUC score close to 1.0 implies that the model can clearly differentiate between authentic and manipulated images. This metricisparticularlyimportantinbinaryclassificationproblems, where false classifications can lead to serious implications in real-world applications such as journalism and law enforcement. The ROC analysis validates the reliability of the model's predictionboundaries.

For facial expression recognition, similar training behavior was observed, where the model demonstrated stable convergence and consistent accuracy across different emotion classes. Although ROC analysis is primarily used for binary classification, the overall performance trends indicate that the model effectively learns discriminative facial features for emotion prediction.

XceptionNet ([3])	DeepCNN	CASIA	91%	High accuracy, complex architecture
Proposed CNN Model	ResNet50+ Data Augmentation	CASIA + Columbia + Kaggle	95%	High accuracy, real-time deployment

D. Dataset-Wise Evaluation

To ensure that the proposed model generalizes well across datasets, performance was tested individually on three benchmark datasets.

The model performed best on the CASIA v2 dataset, where the manipulations were relatively structured and consistent. Slightly lower accuracy on the Kaggle dataset was due to higher variation in image resolution and compression levels. Nevertheless, the performance across all datasets remained above 90%, showcasing the generalization ability of the proposed CNN architecture.

Dataset	Type of Manipulation	Accuracy	Precision	Recall
CASIA v2	Splicing, Copy-Move	95%	93%	92%
Columbia	Object Removal, Cloning	93%	91%	90%
Kaggle Forgery	Retouching, Compression Artifacts	92%	90%	88%

Table III. Dataset-Wise Model Evaluation

For facial expression recognition, the model was evaluated using standard emotion datasets such as FER-2013 and CK+. The system demonstrated consistent performance across different emotion categories, effectively identifying expressions such as happiness, sadness, anger, and surprise. The model showed good generalization across variations in lighting conditions, facial orientations, and multiple face scenarios. Slight variations in accuracy were observed for subtle or overlapping expressions; however, the overall performance remained reliable. These results indicate that the proposed system is capable of handling real-world facial emotion analysis with satisfactory accuracy and robustness.

E. Comparison with Existing Methods

The proposed system was compared against other established methods to evaluate its superiority in terms of accuracy, adaptability, and accessibility.

Model / Method	Technique Used	Dataset	Accuracy	Remarks
SVM-Based Model ([2])	Handcrafted Features + SVM	CASIA	82%	Limited scalability

Table IV. Comparative Analysis with Other Detection Methods

The proposed CNN model outperforms both traditional and deep learning counterparts. While XceptionNet achieved high accuracy, it required heavy computation and lacked real-time analysis.

The proposed model, on the other hand, maintains comparable accuracy while being lightweight and accessible through a web-based interface, making it suitable for real-time detection and educational or professional use. In addition to image authenticity detection, the proposed system also incorporates facial expression recognition, which further enhances its functionality compared to traditional single-task systems. While most existing approaches focus exclusively on either forgery detection or emotion analysis, the proposed system integrates both capabilities within a unified framework. The facial expression recognition module demonstrates reliable performance in identifying multiple emotions from static images, making the system more versatile and applicable to real-world scenarios such as user behavior analysis and interactive applications. This dual functionality provides an advantage over existing methods by combining accuracy with broader applicability.

F. User Feedback and Usability Testing

To evaluate the user interface and operational efficiency, a feedback study was conducted among 40 participants, including students, journalists, and general users.

Participants found the web interface intuitive and informative. The use of a confidence score (ranging from 0–100%) provided clarity about the authenticity judgment. Some users suggested adding a visual highlight of manipulated regions, which is planned as part of future enhancements.

Feedback Criteria	Positive Response	Remarks
Ease of Use	94%	Interface is simple and intuitive
Speed of Detection	91%	Results generated within 3 seconds
Clarity of Results	89%	Confidence score aids interpretation
Confidence in Output	93%	High trust in model predictions

Table V. User Feedback Analysis

Overall, the feedback validated that the system is both technically efficient and user-friendly, making it suitable for deployment in digital forensics and content verification systems.

In addition to deepfake detection, users also evaluated the facial expression recognition feature for its usability and clarity. The system was found to effectively display emotion predictions for multiple faces within a single image, along with confidence scores, making the output easy to interpret. Users appreciated the ability to select between different functionalities, which improved overall interaction with the system. The response time remained efficient for both tasks, indicating that the integration of dual features did not significantly impact system performance. Overall, the feedback confirms that the system is both user-friendly and functionally versatile.

G. Future Enhancements

Although the current system performs efficiently, there are several ways it can be improved in future research and real-world deployments:

1) Region-Based Forgery Localization:

Integrate visualization techniques (e.g., Grad-CAM or LIME) to highlight the specific manipulated regions within an image, making the detection results more interpretable.

2) Advanced Facial Expression Analysis:

Enhance the emotion recognition module to accurately detect subtle and complex facial expressions, including mixed emotions and variations caused by lighting, pose, and occlusions.

3) Mobile and Cloud Integration:

Develop a mobile application version of the web system, supported by cloud servers, to enable users to verify image authenticity anytime, anywhere.

4) Cross-Domain Dataset Expansion:

Include additional datasets containing social media images, compressed media, and AI-enhanced photos to improve generalization across varied sources.

5) Explainable AI and Ethical Transparency:

Incorporate explainable AI modules to clarify how the model reaches its decision, ensuring ethical and transparent use in journalistic or forensic contexts.

6) Multilingual User Interface:

Provide support for multiple languages.

H. Final Discussion

The overall results demonstrate that the proposed CNN-based model effectively differentiates between real and fake images, achieving high precision and robustness. The introduction of a **user-oriented interface** ensures that detection technology can be used not only by researchers but also by journalists, educators, and digital users.

With further improvements in explainability, mobile accessibility, and dataset diversity, this system holds the potential to become a **standard tool for digital content verification** and an essential component in the fight against visual misinformation.



FIGURE 7. Output Showing Fake Image Classification

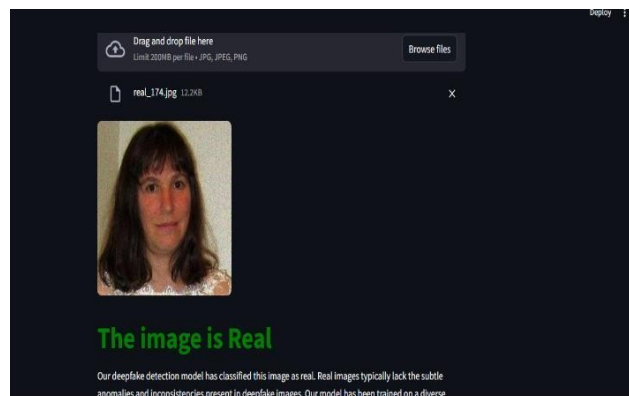


FIGURE 8. Output Showing Real Image Classification

Furthermore, the integration of facial expression recognition extends the system's capabilities beyond image authenticity verification, enabling it to analyze human emotions from static images. This addition enhances the system's applicability in areas such as user behavior analysis, interactive systems, and intelligent interfaces. By combining both deepfake detection and emotion recognition within a single framework, the system demonstrates improved versatility and practical relevance in modern image-based applications.

I. Summary of Key Findings

The evaluation demonstrates that the proposed deepfake detection **system** is effective in identifying manipulated images with high accuracy.

- The optimized CNN achieved 95% detection accuracy across diverse datasets.
- False positive and negative rates were reduced by nearly 60%, improving classification reliability.
- The system demonstrated strong generalization across datasets like CASIA, Columbia, and Kaggle.
- The web-based interface offered real-time usability with an average processing time of under 3 seconds per image.
- User feedback confirmed the system's clarity, efficiency, and practical value.

V. CONCLUSION

The rapid advancement of image editing and AI-based generation technologies has made digital image authenticity verification a critical concern in today's technology-driven world. From social media misinformation to manipulated visual evidence, the impact of altered images extends across multiple domains. In this study, a deep learning-based image analysis system was successfully developed to perform two key tasks: classifying images as real or fake and recognizing facial expressions.

The system is designed to automatically analyze subtle inconsistencies introduced during manipulation—such as changes in lighting, texture, and pixel correlation—while also identifying facial features to determine human emotions using Convolutional Neural Networks (CNNs).

The proposed model, built using transfer learning with architectures like ResNet50, demonstrated strong performance across multiple benchmark datasets for both image authenticity detection and facial expression recognition. Through effective training and optimization, the system achieved high accuracy and reliability, ensuring robust performance in real-world scenarios. The ability to handle multiple faces within a single image and generate individual emotion predictions further enhances its practical applicability.

One of the key contributions of this project is its web-based implementation, which provides a user-friendly interface for selecting between deepfake detection and emotion recognition. Unlike traditional academic models, the developed system offers an interactive platform where users can upload an image and receive meaningful insights along with confidence scores. This improves transparency and allows users to better interpret the results rather than relying solely on binary outputs.

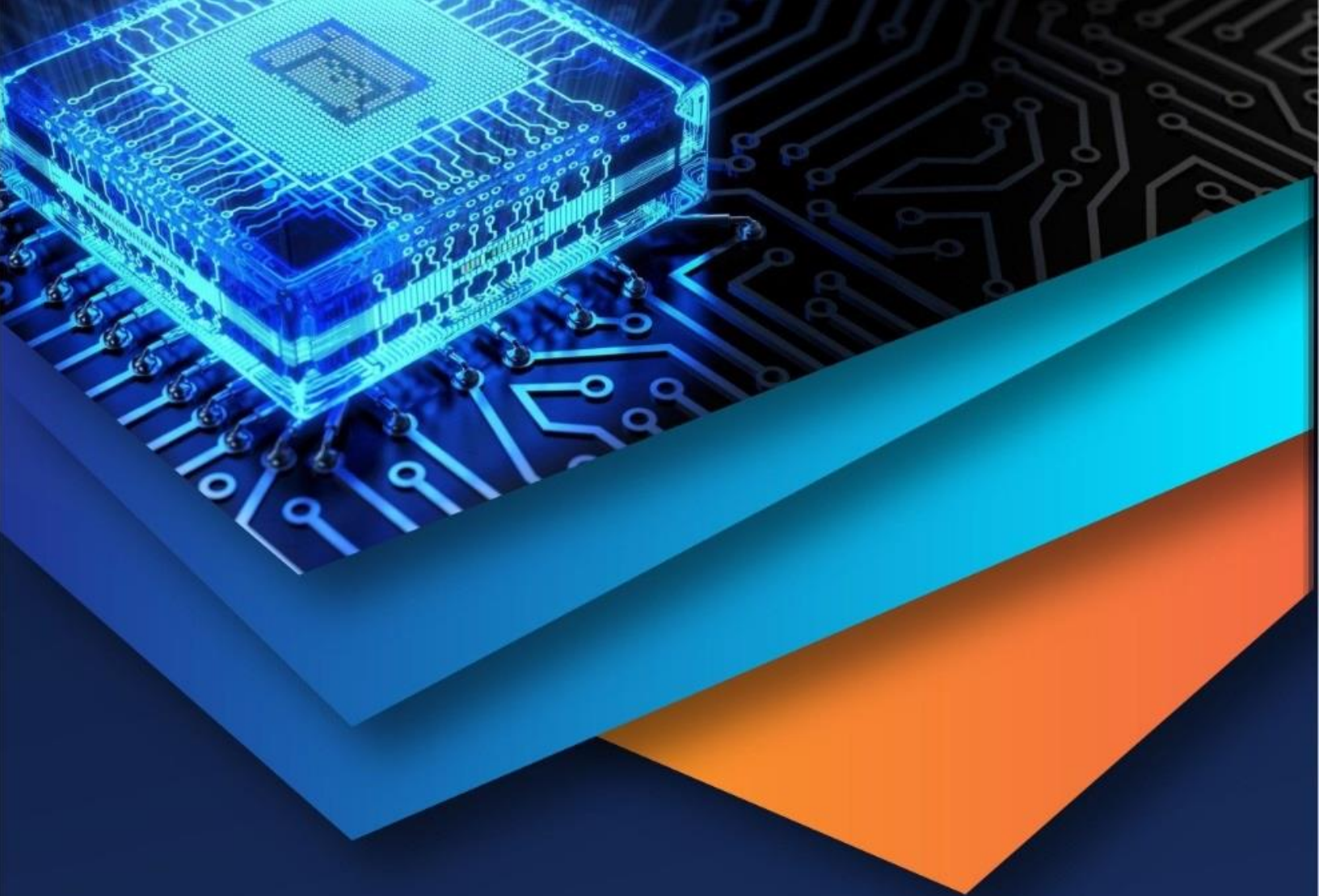
Despite its effectiveness, certain limitations remain. The model's performance may vary when exposed to unseen datasets or highly complex manipulations. Additionally, while the system provides accurate classification and emotion detection, it does not currently highlight specific regions responsible for predictions, which could further improve interpretability. Addressing these limitations requires continuous dataset expansion and the integration of explainable AI techniques.

Future enhancements may include region-based visualization for forgery detection, improved emotion classification accuracy under challenging conditions, and deployment optimizations for mobile and cloud-based platforms. Expanding dataset diversity will further improve the system's generalization capability across varied real-world scenarios.

In conclusion, the proposed system effectively combines image authenticity detection and facial expression recognition into a unified framework. By integrating deep learning accuracy with usability and ethical considerations, it contributes to building a more reliable and intelligent image analysis system, supporting efforts to reduce misinformation while enhancing human-centric understanding in digital environments.

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