A Project Report on

# CIFAKE - IMAGE CLASSIFICATION AND EXPLAINABLE IDENTIFICATION OF AI - GENERATED SYNTHETIC IMAGES

*Submitted in partial fulfillment of the requirement*

*for the award of the degree of*

**BACHELOR OF TECHNOLOGY**

**IN**

**CSE (DATA SCIENCE)**

*Submitted by*

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|---|---|
| S. Annapurna | 21A31A4427 |
| P. Samyuktha | 21A31A4418 |
| B. Srikanth | 21A31A4443 |
| G. Sneha Ratna | 21A31A4410 |
| G. L. Shiva Teja | 21A31A4445 |

Under the esteemed guidance of

**Mrs. D. Chakra Satya Tulasi** M. Tech,

Assistant Professor of CSE (Data Science)

**DEPARTMENT OF CSE (DATA SCIENCE)**

## PRAGATI ENGINEERING COLLEGE

## (AUTONOMOUS)

**(Approved by AICTE, Permanently Affiliated to JNTUK, KAKINADA, Accredited by NBA & NAAC with ‘A+’ Grade)**

**ADB Road, Surampalem, Near Peddapuram, Kakinada District, AP- 533437**

**2021-2025**

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# CERTIFICATE

## DEPARTMENT OF CSE (DATA SCIENCE)

Learning is Supreme Deity

This is to certify that the project report entitled **"CIFAKE – IMAGE CLASSIFICATION AND EXPLAINABLE IDENTIFICATION OF AI – GENERATED SYNTHETIC IMAGES"** is being submitted by **S. Annapurna(**21A31A4427**), P. Samyuktha(**21A31A4418**), B. Srikanth(**21A31A4443**), G. Sneha Ratna(**21A31A4410**), G. L. Shiva Teja(**21A31A4445**)** in partial fulfilment for the award of the Degree of **Bachelor of Technology**, during the year **2021-2025** in Data Science of Pragati Engineering College, for the record of a bonafide work carried out by them.

| Project Supervisor: | Head of the Department: |
|---|---|
| **Mrs. D. Chakra Satya Tulasi** M. Tech | **Mr. M. V. Rajesh** M. Tech, ( Ph.D) |
| Assistant Professor | Associate Professor& HoD |
| Department of CSE (Data Science) | Department of CSE (Data Science) |

# ACKNOWLEDGEMENT

It gives us immense pleasure to express a deep sense of gratitude to our guide **Mrs. D. Chakra Tulasi, Assistant Professor** because of her wholehearted and valuable guidance throughout the report. Without her sustained and sincere effort, this project would not have taken this shape.

We would like to sincerely thank **Mr. M V Rajesh, Associate Professor and Head of the Department of CSE (Data Science)**, for having shown keen interest at every stage of development of our project, encouraged and helped us to overcome various difficulties that we have faced.

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We wish to express sincere gratitude to our beloved and respected **Sri. M. SATISH, Vice-President** and **Sri. M. V. HARANATHA BABU, Director (Management)** and **Dr. P. KRISHNA RAO, Chairman** for giving guidelines and encouragement.

We would like to thank all the faculty members of the Department of CSE (Data Science) for their direct or indirect support for helping us in completion of this report.

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|---|---|
| SINGULURI ANNAPURNA | 21A31A4427 |
| PASUMARTHI SAMYUKTHA | 21A31A4418 |
| BUSI SRIKANTH | 21A31A4443 |
| GOLLA SNEHA RATNA | 21A31A4410 |
| GAMPALA LAKSHMI SHIVA TEJA | 21A31A4445 |

# ABSTRACT

Recent advances in synthetic data have enabled the generation of images with such high quality that human beings cannot distinguish the difference between real-life photographs and Artificial Intelligence (AI) generated images. Given the critical necessity of data reliability and authentication, this project proposes to enhance our ability to recognize AI-generated images through computer vision. A synthetic dataset is generated that mirrors the ten classes of the already available CIFAR-10 dataset using latent diffusion, providing a contrasting set of images for comparison to real photographs. The model is capable of generating complex visual attributes, such as photorealistic reflections in water. The two sets of data present a binary classification problem regarding whether the photograph is real or generated by AI. This project proposes the use of a Convolutional Neural Network (CNN) to classify the images into two categories: Real or Fake. Following hyper-parameter tuning and the training of 36 individual network topologies, the optimal approach demonstrated strong classification performance. Explainable AI is implemented via Gradient Class Activation Mapping to explore which features within the images are useful for classification, providing insights into how neural networks distinguish AI-generated images and helping improve future detection models.

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# CHAPTER-1

# INTRODUCTION

# INTRODUCTION

The field of synthetic image generation by Artificial Intelligence (AI) has developed rapidly in recent years, and the ability to detect AI-generated photos has also become a critical necessity to ensure the authenticity of image data. Within recent memory, generative technology often produced images with major visual defects that were noticeable to the human eye, but now we are faced with the possibility of AI models generating high-fidelity and photorealistic images in a matter of seconds. The AI-generated images are now at the quality level needed to compete with humans and win art competitions. Latent Diffusion Models (LDMs), a type of generative model, have emerged as a powerful tool to generate synthetic imagery. These recent developments have caused a paradigm shift in our understanding of creativity, authenticity, and truth. This has led to a situation where consumer-level technology is available that could quite easily be used for the violation of privacy and to commit fraud. These philosophical and societal implications are at the forefront of the current state of the art, raising fundamental questions about the nature of trustworthiness and reality.

Recent technological advances have enabled the generation of images with such high quality that human beings cannot tell the difference between a real-life photograph and an image that is no more than a hallucination of an artificial neural network’s weights and biases. Generative imagery that is indistinguishable from photographic data raises both ontological questions, which concern the nature of being, and epistemological questions, surrounding the theories of methods, validity, and scope. Ontologically, given that humans cannot tell the difference between images from cameras and those generated by AI models such as an Artificial Neural Network, there are serious epistemological questions surrounding the reliability of human knowledge and the ethical implications of the misuse of these technologies. These implications suggest that we are in growing need of a system that can aid us in recognizing real images versus those generated by AI. This project explores the potential of using computer vision to enhance our newfound inability to recognize the difference between real photographs and AI-generated ones.

Following the generation of a synthetic equivalent to such data, we will then explore the output of the model before finally implementing methods of differentiation between the two types of images. There are several scientific contributions with multidisciplinary and social implications that arise from this project. First, a dataset called CIFAKE is generated with latent diffusion and released to the research community. The CIFAKE dataset provides a contrasting set of real and fake photographs and contains 120,000 images (60,000 images from the existing CIFAR-10 dataset and 60,000 images generated for this project), making it a valuable resource for researchers in the field. Second, this project proposes a method to improve our waning human ability to recognize AI-generated images through computer vision, using the CIFAKE dataset for classification. Finally, the use of Explainable AI (XAI) is proposed to further our understanding of the complex processes involved in synthetic image recognition, as well as the visualization of important features within those images. These scientific contributions provide important steps forward in addressing the modern challenges posed by rapid developments in technology and have significant implications for ensuring the authenticity and trustworthiness of data

# CHAPTER -2

# LITERATURE SURVEY

# LITERATURE SURVEY

**"AI-generated artwork has sparked debate over creativity and authorship in digital content."** K. Roose [1], reports on an AI-generated image that won an art competition, stirring discussions on the authenticity and value of machine-generated art. The paper reflects growing concerns from artists regarding AI's role in creative domains.

R. Rombach et al. [2], present Latent Diffusion Models (LDMs) that enable high-resolution image synthesis. These models reduce computational demands by working in latent space while producing photorealistic outputs, marking a significant advancement in generative AI.

**"Psychological insights can help understand susceptibility to fake content online."** G. Pennycook and D. G. Rand [3], explore how cognitive biases and low analytical thinking increase the likelihood of believing fake news. The study emphasizes the importance of individual behavior in combating misinformation.

B. Singh and D. K. Sharma [4], utilize a multi-modal machine learning approach for detecting fake images on social media. Their model combines visual and textual cues to enhance prediction accuracy in identifying deceptive posts.

**"Statistical irregularities in image features can indicate synthetic origins."** N. Bonettini et al. [5], investigate the use of Benford's Law to detect GAN-generated images. Their findings suggest that generative models often fail to reproduce natural statistical patterns, providing a potential detection method.

D. Deb, J. Zhang, and A. K. Jain [6], propose AdvFaces, a framework for adversarial face synthesis that evaluates vulnerabilities in face recognition systems, shedding light on how AI can both deceive and challenge biometric security.

**"AI-generated biometric attacks raise concerns over system robustness and security."** M. Khosravy et al. [7], analyze model inversion attacks under gray-box conditions on face recognition systems. Their study highlights how attackers can exploit deep learning models to reconstruct facial images from embeddings.

J. J. Bird, A. Naser, and A. Lotfi [8], assess the resilience of signature verification systems against robotic and GAN-based attacks. Their research emphasizes the growing threat of generative models in identity fraud.

**“Text-to-image generation achieves zero-shot capabilities through transformer-based models.”**

A. Ramesh et al. [9], introduce DALL·E, a zero-shot text-to-image generation model that combines transformers with image and text understanding. This model illustrates how generative systems can create meaningful visuals without fine-tuning.

C. Saharia et al. [10], develop a photorealistic text-to-image diffusion model, uniting deep language models with diffusion processes. Their approach pushes the boundaries of visual realism and semantic alignment in generative tasks.

**“Foundation models can be adapted to specialized domains like medical imaging through fine-tuning.”**

P. Chambon et al. [11], explore the adaptation of pretrained vision-language models to the medical imaging field. Their work demonstrates how fine-tuning enables general-purpose models to perform well on domain-specific tasks.

F. Schneider et al. [12], introduce **Moûsai**, a text-to-music generation system using latent diffusion with long-context understanding. The model captures musical coherence by leveraging deep language embeddings and diffusion techniques.

**“Human–machine collaborative creativity can be enabled through interactive generative models.”**

C. Guo et al. [15], propose **ArtVerse**, a framework that integrates human input with AI-driven painting in the Metaverse. The model allows users to interact with diffusion systems in real time to co-create art, bridging the gap between human intuition and machine creativity.

# CHAPTER-3

# SYSTEM ANALYSIS

# SYSTEM ANALYSIS

## 3.1 Existing System

Existing systems for detecting AI-generated images include various advanced techniques. Latent Diffusion Models (LDMs), such as Stable Diffusion, DALL-E, and Imagen, generate high-fidelity synthetic images with complex visual attributes like reflections, motion blur, and depth of field, but they also pose challenges for detection systems. The DE-FAKE method leverages digital fingerprints and Fourier transforms to identify synthetic images, while EfficientNet and Vision Transformers offer competitive performance metrics, such as F1 scores and AUC, on datasets like the Deep Fake Detection Challenge. Optical Flow Techniques have been employed for detecting synthetic human faces, achieving moderate accuracy, while hybrid CNN-LSTM models integrate convolutional and temporal features for deepfake video detection. Although these methods demonstrate promising capabilities, they often struggle to generalize across diverse datasets, and many rely on detectable visual glitches that are becoming increasingly rare with advanced generative models.

**LIMITATIONS:**

**Performance on High-Quality Synthetic Images:** Many methods rely on detectable visual glitches, which are becoming increasingly rare with advanced generative models.

**Generalizability:** Existing methods are often designed for specific datasets or image types (e.g., human faces, specific categories).Limited adaptability to diverse image types, such as clinical scans or other domains.

**Black-Box Nature:** Most models are not interpretable and fail to explain predictions, making them less reliable for sensitive applications like fraud detection.

Limited Focus on Subtle Features: Current models often miss subtle imperfections like small pixel disparities or background anomalies that advanced synthetic images present.

**Accuracy Challenges:** Methods like DE-FAKE and Optical Flow Techniques, while promising, have relatively low accuracy compared to human-like discernment, especially for images.

## 3.2 Proposed System

The proposed system employs a robust Convolutional Neural Network (CNN) to classify images as either real or synthetic. This model is fine-tuned using hyper-parameter optimization, achieving an impressive accuracy of 87.14%. The CNN leverages convolutional layers to extract key features and dense layers to make accurate classifications, providing a significant improvement over existing detection methods. To enhance transparency, the system incorporates Gradient Class Activation Mapping (Grad-CAM), an explainable AI technique. Grad-CAM generates heat maps that visually highlight the regions within images that contribute most to the model's classification. This approach not only improves interpretability but also builds user trust by offering insights into how decisions are made.

The study introduces a new dataset, CIFAKE, comprising 120,000 images, including 60,000 real images from the CIFAR-10 dataset and 60,000 synthetic images generated using Stable Diffusion. This dataset is diverse and high-quality, representing real-world scenarios and ensuring the model is well-trained to handle complex classifications.

A dynamic retraining mechanism is also proposed to ensure the system adapts to evolving challenges posed by advanced generative models. By regularly updating the dataset with new real and synthetic images, the system maintains robustness and effectiveness against novel synthetic image features.

In addition to its technical features, the system focuses on detecting subtle visual anomalies, such as minor glitches and imperfections, often overlooked by existing methods. This makes the system highly effective in identifying high-fidelity synthetic images. Overall, the proposed system combines accuracy, adaptability, and explainability, making it a comprehensive solution for detecting AI-generated synthetic images.

**ADVANTAGES:**

**Higher Classification Accuracy:** The proposed CNN achieves a classification accuracy of 87.14%. outperforming methods like DE-FAKE and Optical Flow Techniques, which struggle with high-fidelity synthetic images.

**Enhanced Explainability:** Grad-CAM enables users to interpret model decisions by visualizing key features in the image. This is a significant improvement over existing black-box models like EfficientNet and Vision Transformers, which lack explainability.

**Adaptability with Dynamic Retraining:** Unlike static models that degrade in performance with evolving synthetic image generation techniques, the proposed system incorporates a dynamic retraining mechanism to adapt to novel patterns and features.

**Comprehensive Dataset:** The CIFAKE dataset is specifically designed for this study and provides high-quality synthetic and real image pairs. This contrasts with existing datasets, which are often limited in diversity and scalability.

**Focus on Subtle Imperfections:** The proposed system leverages Grad-CAM to detect minute visual glitches or background anomalies in synthetic images, a capability lacking in many existing methods reliant on human-visible defects.

**Broader Applicability:** While existing methods often focus on specific domains (e.g., human faces or videos), the proposed approach is versatile and can be extended to various datasets and applications, including medical imaging and security systems.

**Scalability and Adaptability:** The system's ability to process vast datasets ensures scalability for handling large volumes of patient or compound data, making it suitable for diverse medical and pharmaceutical applications.

**Advancement of Personalized Medicine:** By tailoring treatments to an individual's unique genetic makeup and health profile, the system promotes a shift towards personalized medicine, improving patient satisfaction and healthcare quality.

**Enhanced Safety and Efficacy:** The use of ML models to predict individual responses to treatments ensures better safety profiles for drugs and optimizes efficacy for diverse patient populations

# CHAPTER - 4
# SYSTEM DESIGN

# SYSTEM DESIGN

## 4.1 SYSTEM ARCHITECTURE

**Key Steps in the Process:**

1. **Data-Gathering:**

- Collects image data from various sources.
- Ensures a diverse dataset containing both real and fake images.

2. **Image-Processing:**

- Performs preprocessing tasks such as resizing, normalization, and augmentation.
- Enhances image quality to improve model accuracy.

3. **Image-Classification:**

- Applies a classification model to categorize images.
- Extracts high-level features from images for further analysis.

4. **Self-Supervised Learning with Transformer Model:**

- Uses a self-supervised learning approach to train a Transformer-based model.
- Learns meaningful representations from image data without labeled examples.

5. **Self-Supervised Learning Refinement:**

- Further refines the model’s ability to differentiate real and fake images.
- Enhances feature representations through iterative learning.

6. **CIFAKE Prediction:**

- Uses the trained model to classify images as real or fake.
- Generates a final prediction based on learned features.

7. **Final Decision:**

- If classified as **Real**, the image is considered authentic.
- If classified as **Fake**, the image is flagged as manipulated or synthetic.

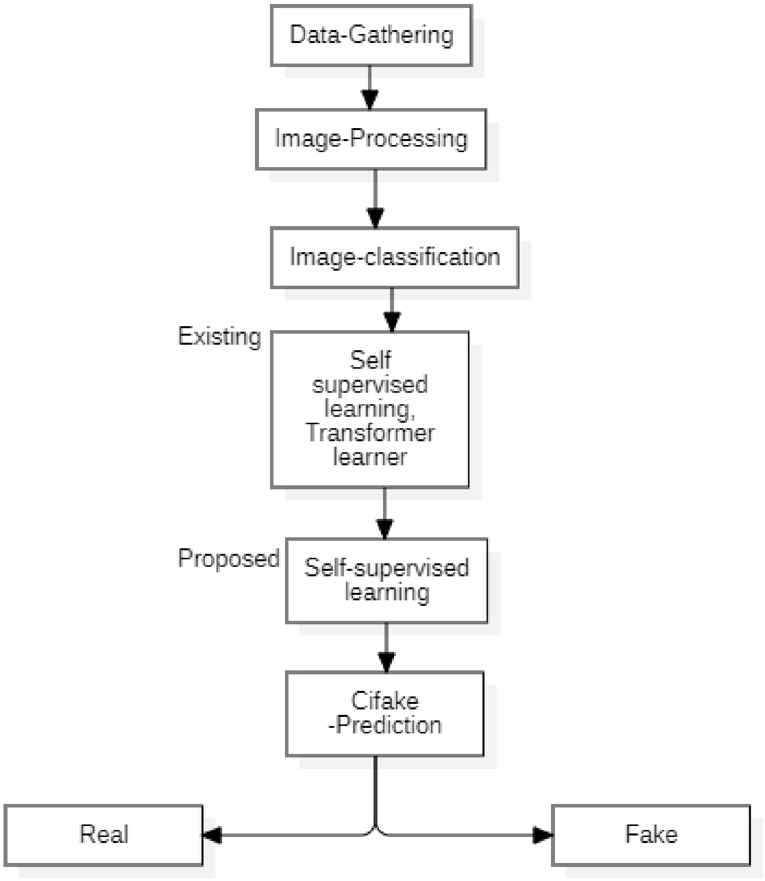


*Fig. 4.1: System Architecture*

## 4.2 UML REPRESENTATION

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

**GOALS:**

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.

2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language
5. Encourage the growth of OO tools market.

### 4.2.1 Use case Diagram:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

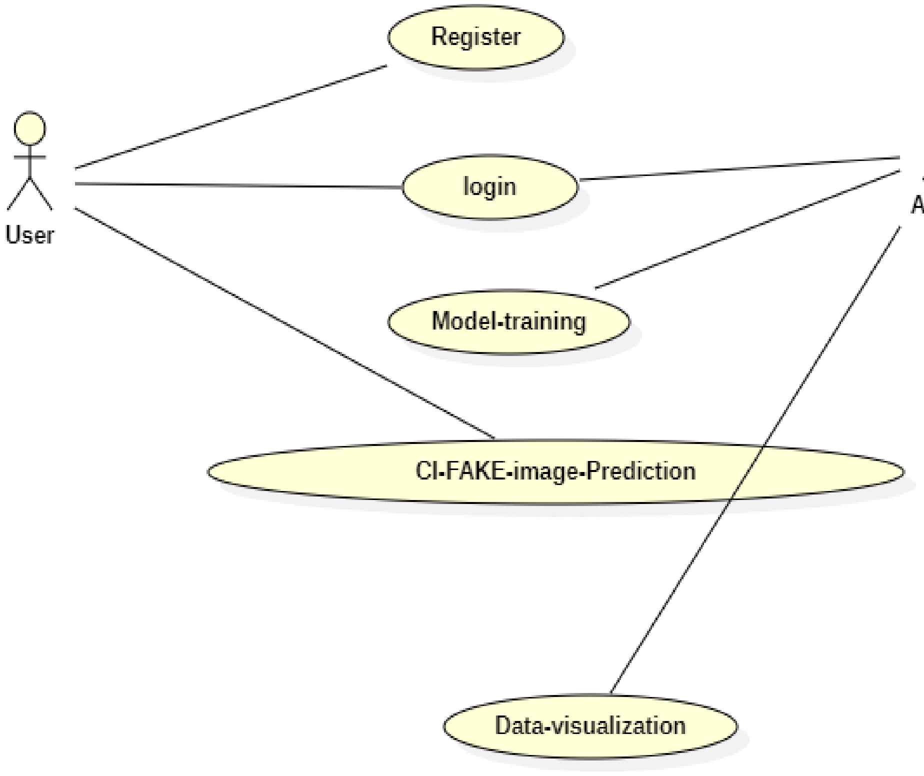


*Fig 4.2 Use Case Diagram*

### 4.2.2 Sequence diagram:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

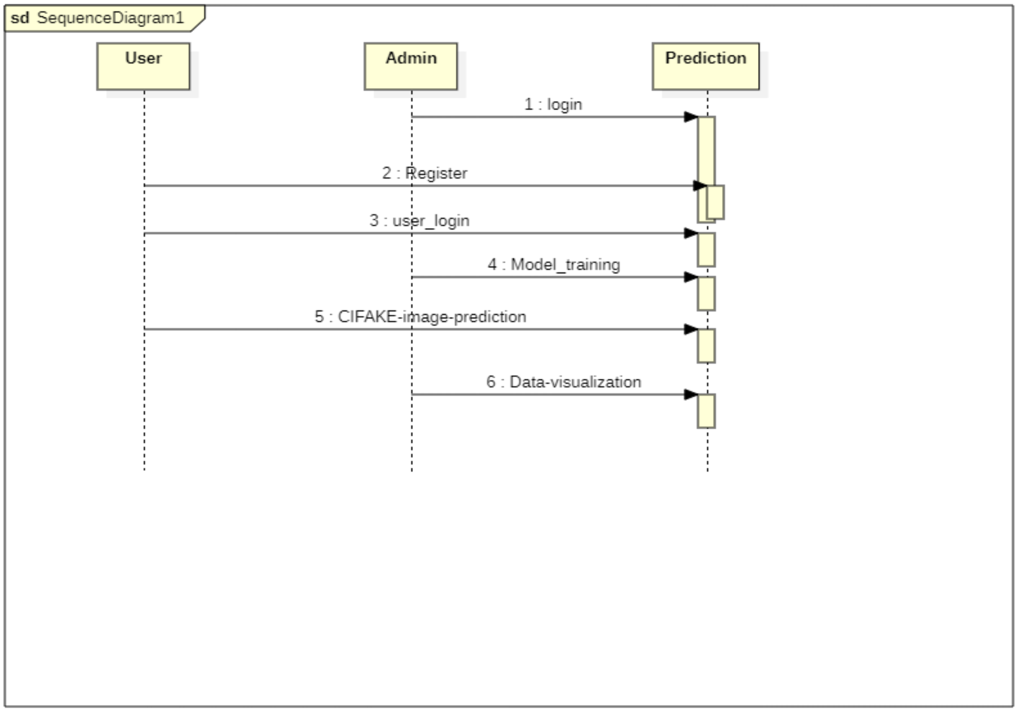


*Fig 4.3 Sequence Diagram*

### 4.2.3 Deployment Diagram:

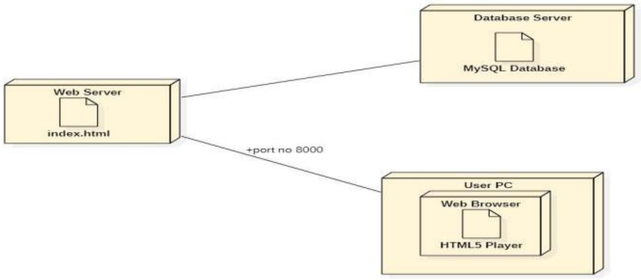


*Fig 4.4 Deployment Diagram*

### 4.2.4 Activity Diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modelling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

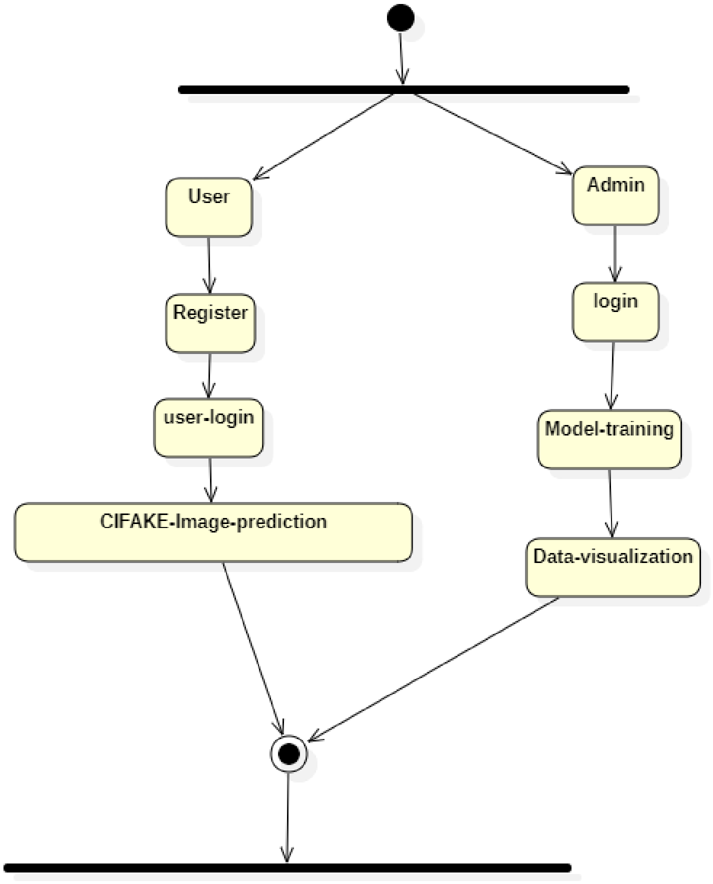


*Fig 4.5 Activity Diagram*

### 4.2.5 Class Diagram:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

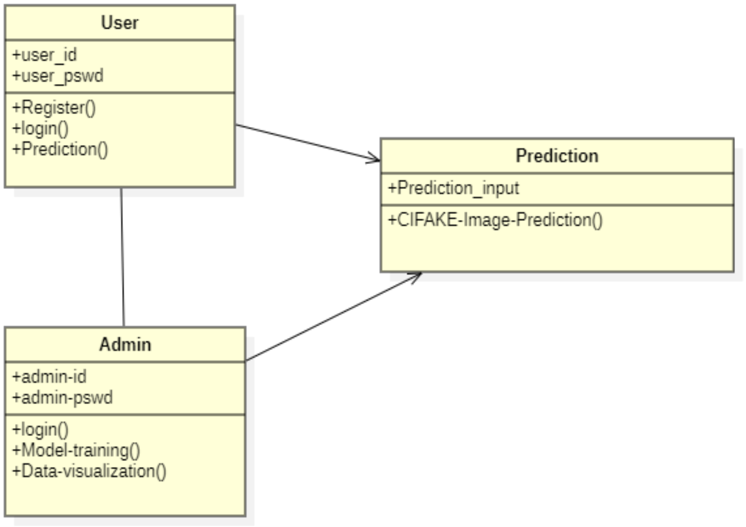


*Fig 4.6 Class Diagram*

### 4.2.6 Flow Chart Diagram:

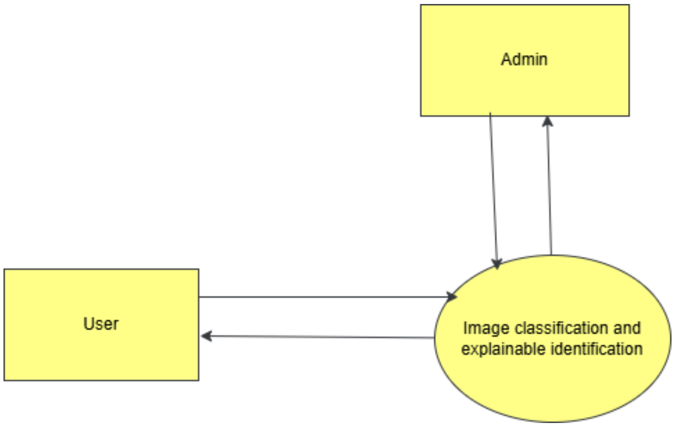


*Fig 4.7 Flow chart  Diagram*

# CHAPTER- 5

# SYSTEM IMPLEMENTATION

# SYSTEM IMPLEMENTATION

## 5.1 Modules:

**Data Preprocessing:** Data preprocessing involves preparing real and synthetic image datasets for classification. In this paper, 60,000 real images are sourced from the CIFAR-10 dataset, and 60,000 synthetic images are generated using Stable Diffusion, a Latent Diffusion Model (LDM). Both datasets are resized to a resolution of 32x32 pixels using bilinear interpolation to ensure consistency. Class labels ("REAL" for authentic images and "FAKE" for synthetic images) are assigned, and data augmentation techniques, such as flipping and rotation, are applied to improve model generalization during training.

**Model Training:** The study employs a Convolutional Neural Network (CNN) for binary classification. The network architecture includes multiple layers of convolutional filters (e.g., {16, 32, 64, 128}) followed by pooling layers and fully connected layers. Hyper-parameter tuning is performed across 36 network configurations to identify the optimal topology, which achieves a classification accuracy of 87.14%. The model is trained using the binary cross-entropy loss function and back propagation, with the Adam optimizer fine-tuned for efficient gradient descent.

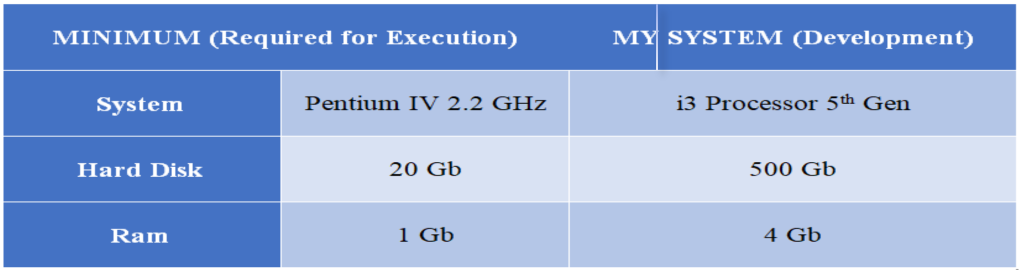
**Dynamic Retraining Mechanism:** A dynamic retraining mechanism is proposed to enhance model robustness against evolving synthetic generation techniques. By continuously updating the dataset with new real and synthetic images, particularly those generated by more advanced models, the system adapts to emerging challenges. Retraining occurs periodically to ensure the classifier remains effective against novel synthetic image features or patterns.

**Anomaly Detection:** The paper incorporates Explainable AI techniques like Gradient Class Activation Mapping (Grad-CAM) to detect anomalies in synthetic images. Grad-CAM highlights regions in the image that contribute most to the classification decision. For synthetic images, the model often focuses on subtle visual glitches or background imperfections that are challenging.

**User Interface and Reporting:** A user-friendly interface is suggested for displaying classification results and insights. The interface includes heat maps generated by Grad-CAM to visually interpret model predictions. Reports summarize key metrics, including accuracy, precision, recall, and F1 scores, providing actionable feedback. The interface also enables users to upload new images for classification and view detailed explanations for each prediction, ensuring transparency and trust in the system's decisions.

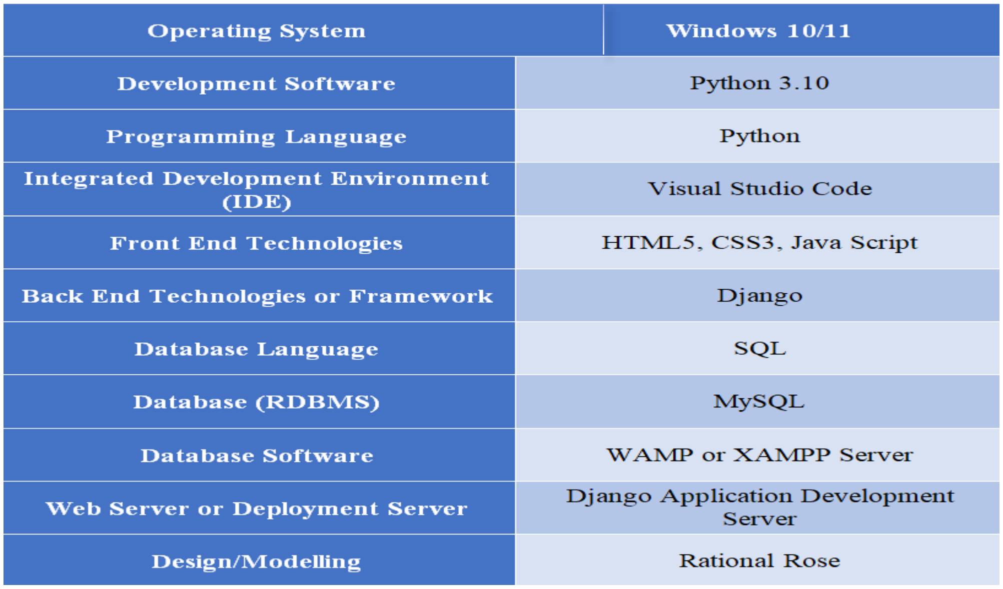
## 5.2 SYSTEM REQUIREMENTS

### HARDWARE REQUIREMENTS:



| MINIMUM (Required for Execution) | | MY SYSTEM (Development) |
|---|---|---|
| System | Pentium IV 2.2 GHz | i3 Processor 5th Gen |
| Hard Disk | 20 Gb | 500 Gb |
| Ram | 1 Gb | 4 Gb |

### SOFTWARE REQUIREMENTS:



| Operating System | Windows 10/11 |
|---|---|
| Development Software | Python 3.10 |
| Programming Language | Python |
| Integrated Development Environment (IDE) | Visual Studio Code |
| Front End Technologies | HTML5, CSS3, Java Script |
| Back End Technologies or Framework | Django |
| Database Language | SQL |
| Database (RDBMS) | MySQL |
| Database Software | WAMP or XAMPP Server |
| Web Server or Deployment Server | Django Application Development Server |
| Design/Modelling | Rational Rose |

# CHAPTER - 6

# SYSTEM TESTING

# SYSTEM TESTING

## 6.1 TYPES OF TESTING

**Functional Testing:** Functional testing is a crucial part of software testing that focuses on verifying that a system or application meets its functional requirements. In the context of our project, functional testing ensures that the system behaves as expected and correctly identifies fraudulent activities. Here's how you can perform functional testing for such a system:

a) **Test Case Identification:** Identify functional requirements: Review the system's specifications, user stories, and use cases to understand the expected behavior of the fraud detection system. Develop test cases based on different scenarios that the system should support, such as detecting various types of fraudulent activities (e.g., fake reviews, malware-containing apps, coordinated fraud schemes).

b) **Test Environment Setup:** Set up a testing environment that closely resembles the production environment, including the necessary infrastructure, data, and dependencies. Ensure that the testing environment is isolated from the production environment to prevent any impact on real users or data.

c) **Test Execution:** Execute the identified test cases systematically, following the predefined test scenarios. Provide input data or stimuli to the system and observe its responses. Verify that the system behaves according to the expected outcomes specified in the test cases. Record any deviations, defects, or unexpected behaviors encountered during testing.

### Unit Testing

Unit testing is a type of software testing which is done on an individual unit or component to test its corrections. Typically, Unit testing is done by the developer at the application development phase. Each unit in unit testing can be viewed as a method, function, procedure, or object. Unit testing is important because we can find more defects at the unit test level.

Unit testing in the context of a project like "CIFAKE – Image Classification and Explainable Identification of AI – Generated Synthetic Images" would focus on testing individual units or components of the system in isolation. Since this project likely involves various components such as data preprocessing, feature engineering, model training, and prediction, each of these would be subject to unit testing. Here's how unit testing could be approached for each component:

a) **DataPreprocessing Unit Testing**: Test individual data preprocessing functions/methods such as data cleaning, normalization, and encoding. Verify that each function/method handles edge cases and unexpected inputs correctly. Mock input data to simulate different scenarios (e.g., missing values, outliers) and validate the output.

b) **Model Training Unit Testing**: Test functions/methods responsible for training machine learning models. Mock training data and verify that models are trained successfully. Validate that hyper-parameter tuning functions/methods work as expected. Ensure that model evaluation metrics are computed correctly.

c) **Prediction Unit Testing**: Test functions/methods responsible for making predictions on new transaction data. Mock input data and verify that predictions are generated accurately. Test edge cases such as empty input or unexpected data formats. Validate that prediction outputs adhere to expected formats and conventions.

d) **System Testing:** System testing is types of testing where tester evaluates the whole system against the specified requirements.

### End to End Testing

It involves testing a complete application environment in a situation that mimics real-world use, such as interacting with a database, using network communications, or interacting with other hardware, applications, or systems if appropriate. System testing in our project involves testing the integrated system as a whole to ensure that it meets its specified requirements and functions correctly in its intended environment.

## 6.2 TEST CASES

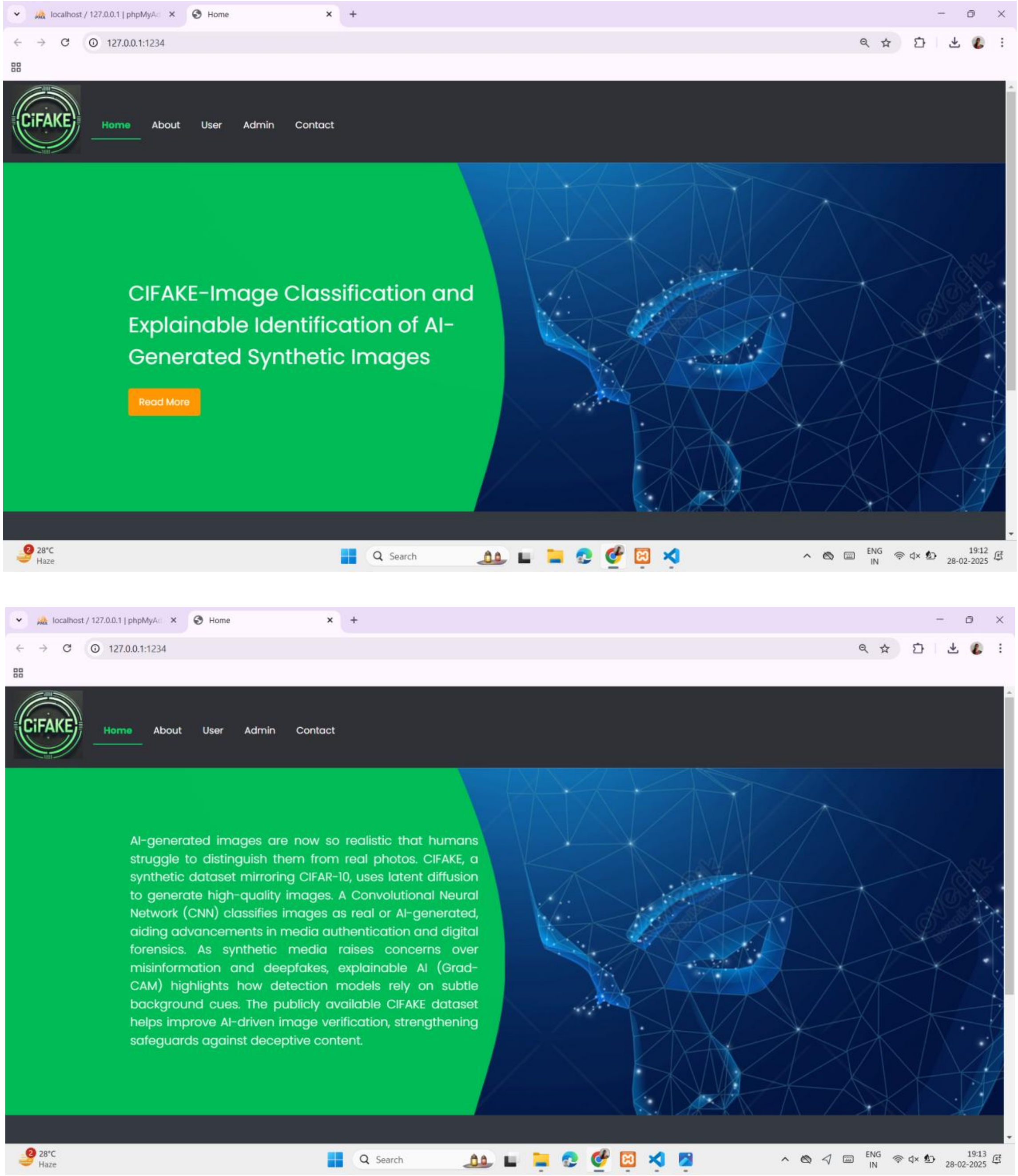
| **Test Case ID** | **Pre-Conditions** | **Test Steps** | **Test Result** | **Pass/Fail** |
|---|---|---|---|---|
| TC_U01 | After successful user registration | 1. Enter valid credentials<br>2. Click "Login" | User successfully logged in | Pass |
| TC_U02 | After successful user registration | 1. Enter incorrect username/password<br>2. Click "Login" | Error message **"Invalid credentials"** appears | Pass |
| TC_U03 | After successful login | 1. Click the **"Result"** button | Prediction results displayed with confidence score and visualization | Pass |
| TC_U04 | After successful login | 1. Click **"Result"** without selecting an image | Error message **"please upload image"** appears | Fail |
| TC_U05 | After successful login | 1. Submit prediction with incorrect image format (e.g., .txt) | Error message **"Invalid file format"** appears | Pass |
| TC_U06 | After successful login | 1. Click "Logout"<br>2. Try to access the Home page | User is still able to access dashboard (Session not ended) | Fail |

| | | | | |
|---|---|---|---|---|
| TC_A01 | Before successful login of admin | 1.Enter incorrect username/password<br>2.Click “Login” | Error message **“You’re trying to enter wrong details”** appears. | Pass |
| TC_A02 | After successful Login of admin | 1.Open Dashboard<br>2.Go to User Management<br>3.Accept pending users | Registered user gains access. | Pass |
| TC_A03 | After successful Login of admin | 1.Open **Algorithm Panel**<br>2.Click “Run Algorithm” | Algorithm executes successfully. | Pass |
| TC_A04 | After successful Login of admin | 1.Click “Run Algorithm”<br>2.Check whether accuracy and precision scores are available for algorithm | Accuracy and precision scores are displayed. | Pass |
| TC_A05 | After successful Login of admin | 1.Click “Logout”<br>2.Try to access the Home Page | Admin is still able to access the dashboard (Session not ended). | Fail |

# CHAPTER -7

# SCREENSHOTS

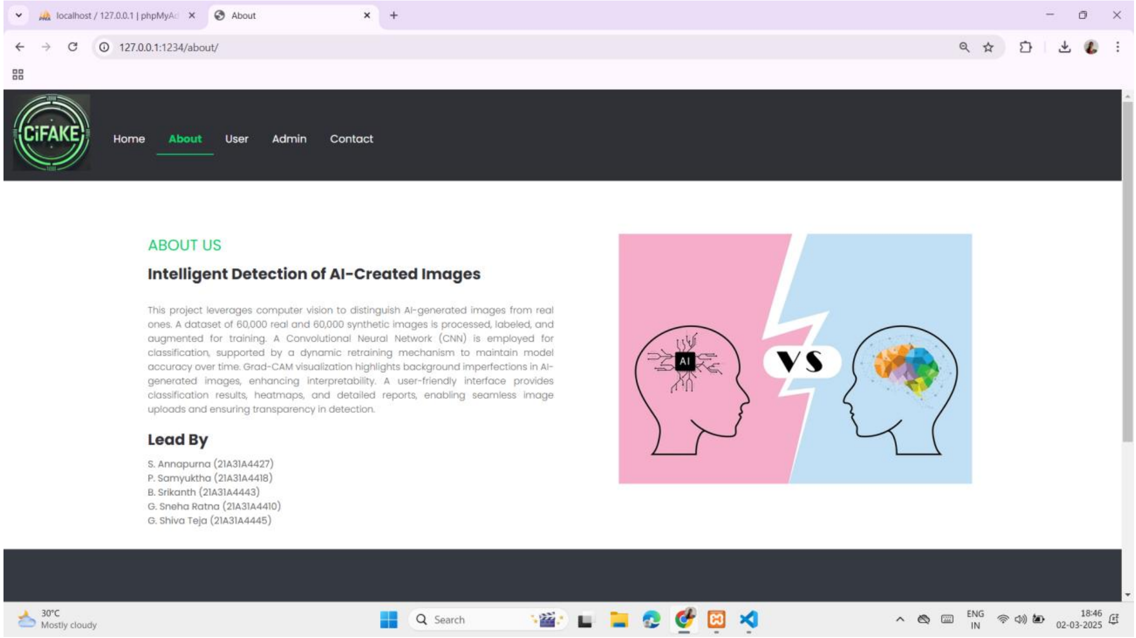
# SCREENSHOTS



CIFAKE-Image Classification and Explainable Identification of AI-Generated Synthetic Images

AI-generated images are now so realistic that humans struggle to distinguish them from real photos. CIFAKE, a synthetic dataset mirroring CIFAR-10, uses latent diffusion to generate high-quality images. A Convolutional Neural Network (CNN) classifies images as real or AI-generated, aiding advancements in media authentication and digital forensics. As synthetic media raises concerns over misinformation and deepfakes, explainable AI (Grad-CAM) highlights how detection models rely on subtle background cues. The publicly available CIFAKE dataset helps improve AI-driven image verification, strengthening safeguards against deceptive content.

*Fig. 7.1 Home Page*



ABOUT US

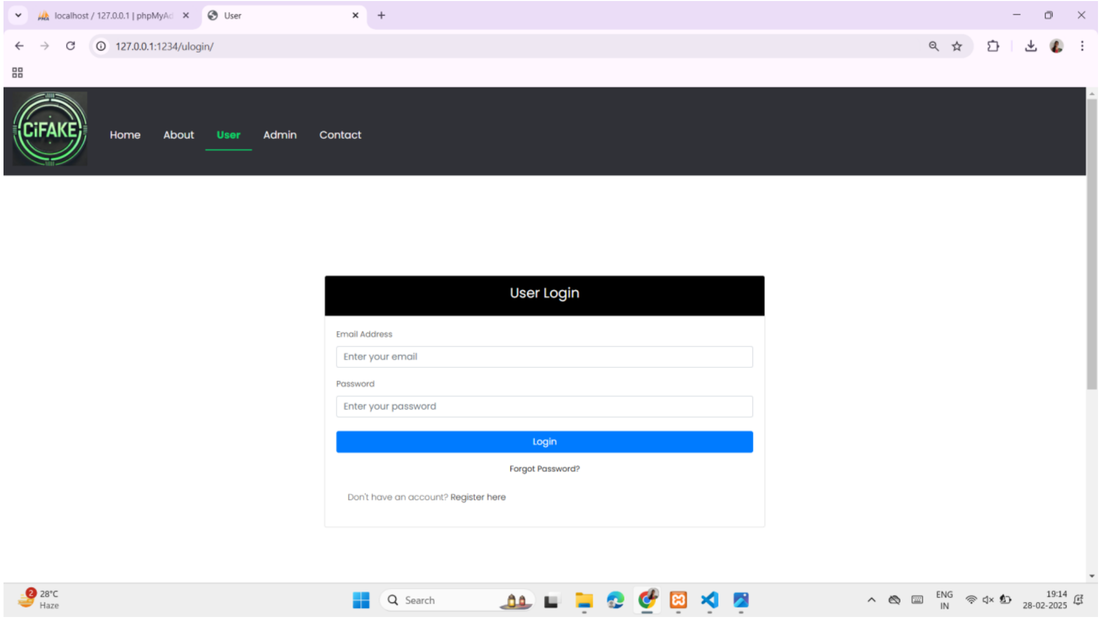
Intelligent Detection of AI-Created Images

This project leverages computer vision to distinguish AI-generated images from real ones. A dataset of 60,000 real and 60,000 synthetic images is processed, labeled, and augmented for training. A Convolutional Neural Network (CNN) is employed for classification, supported by a dynamic retraining mechanism to maintain model accuracy over time. Grad-CAM visualization highlights background imperfections in AI-generated images, enhancing interpretability. A user-friendly interface provides classification results, heatmaps, and detailed reports, enabling seamless image uploads and ensuring transparency in detection.

Lead By

S. Annapurna (21A31A4427)
P. Samyuktha (21A31A4418)
B. Srikanth (21A31A4443)
G. Sneha Ratna (21A31A4410)
G. Shiva Teja (21A31A4445)

*Fig. 7.2 About Page*



User Login

Email Address

Enter your email

Password

Enter your password

Login

Forgot Password?

Don't have an account? Register here

*Fig. 7.3 User Login*

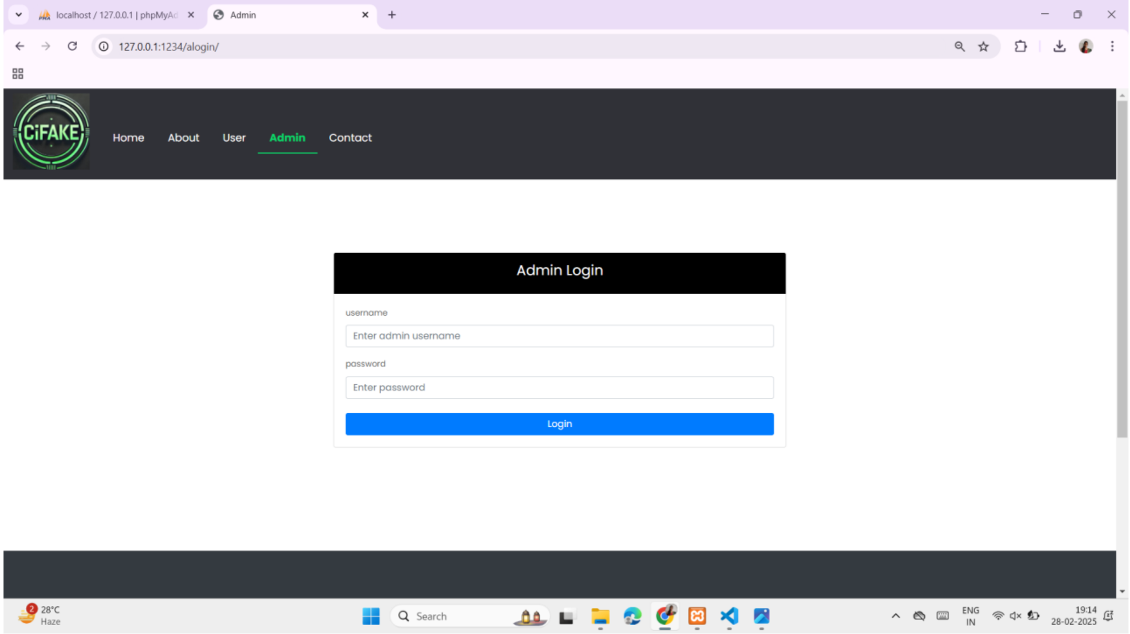
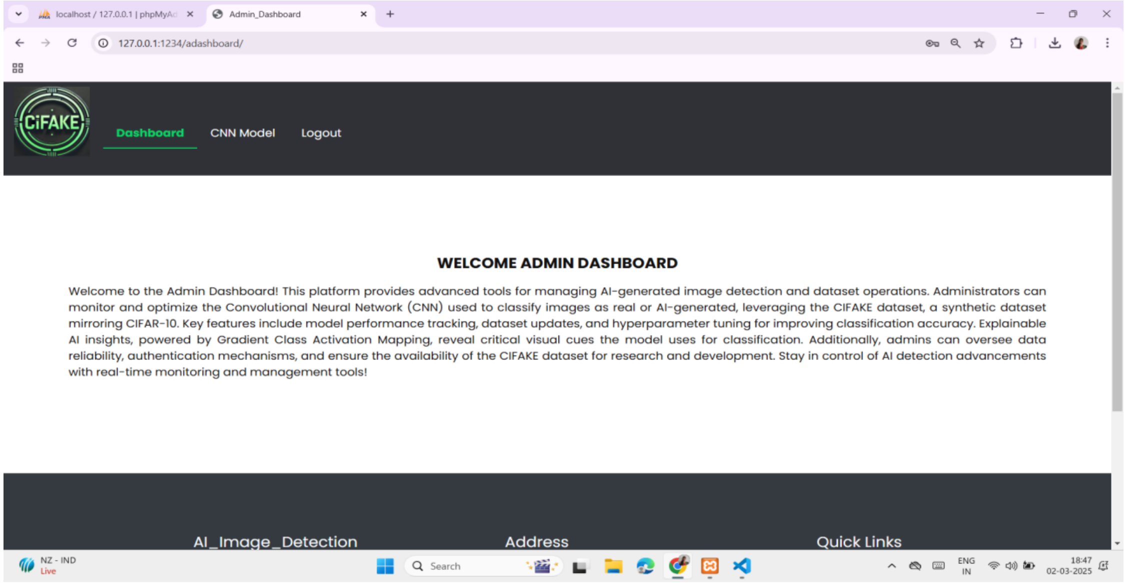


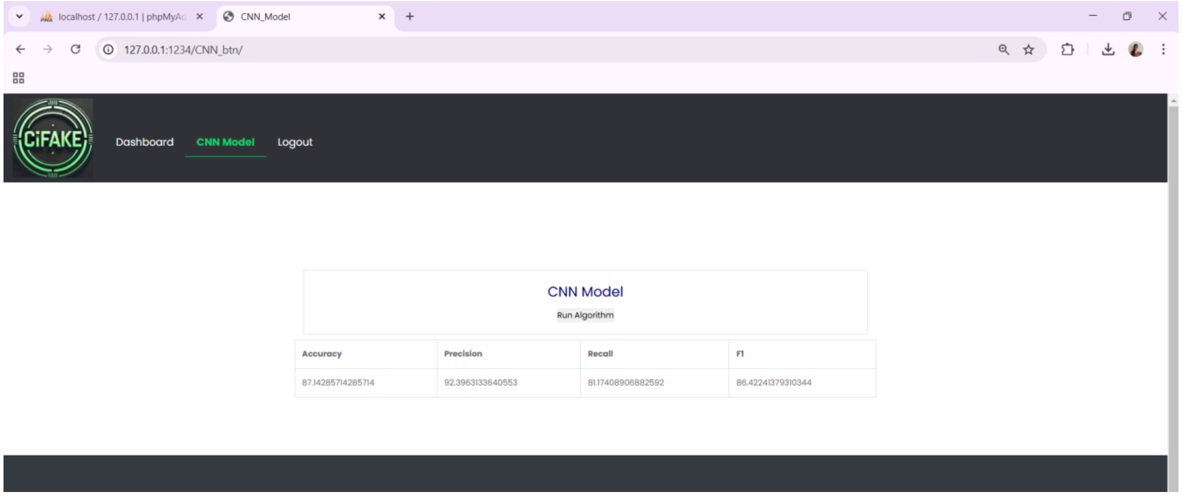
*Fig. 7.4 Admin Login*



WELCOME ADMIN DASHBOARD

Welcome to the Admin Dashboard! This platform provides advanced tools for managing AI-generated image detection and dataset operations. Administrators can monitor and optimize the Convolutional Neural Network (CNN) used to classify images as real or AI-generated, leveraging the CIFAKE dataset, a synthetic dataset mirroring CIFAR-10. Key features include model performance tracking, dataset updates, and hyperparameter tuning for improving classification accuracy. Explainable AI insights, powered by Gradient Class Activation Mapping, reveal critical visual cues the model uses for classification. Additionally, admins can oversee data reliability, authentication mechanisms, and ensure the availability of the CIFAKE dataset for research and development. Stay in control of AI detection advancements with real-time monitoring and management tools!

*Fig. 7.5 Admin Dashboard*

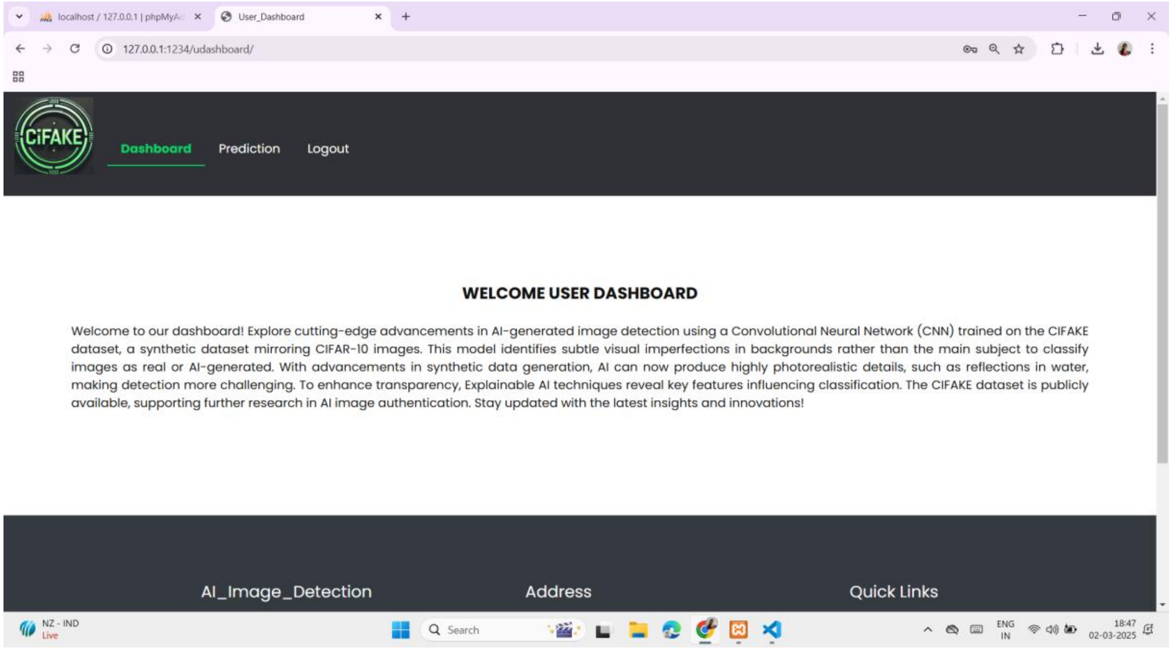


CNN Model

Run Algorithm

| Accuracy | Precision | Recall | F1 |
|---|---|---|---|
| 87.14285714285714 | 92.3963133640553 | 81.17408906882592 | 86.42241379310344 |

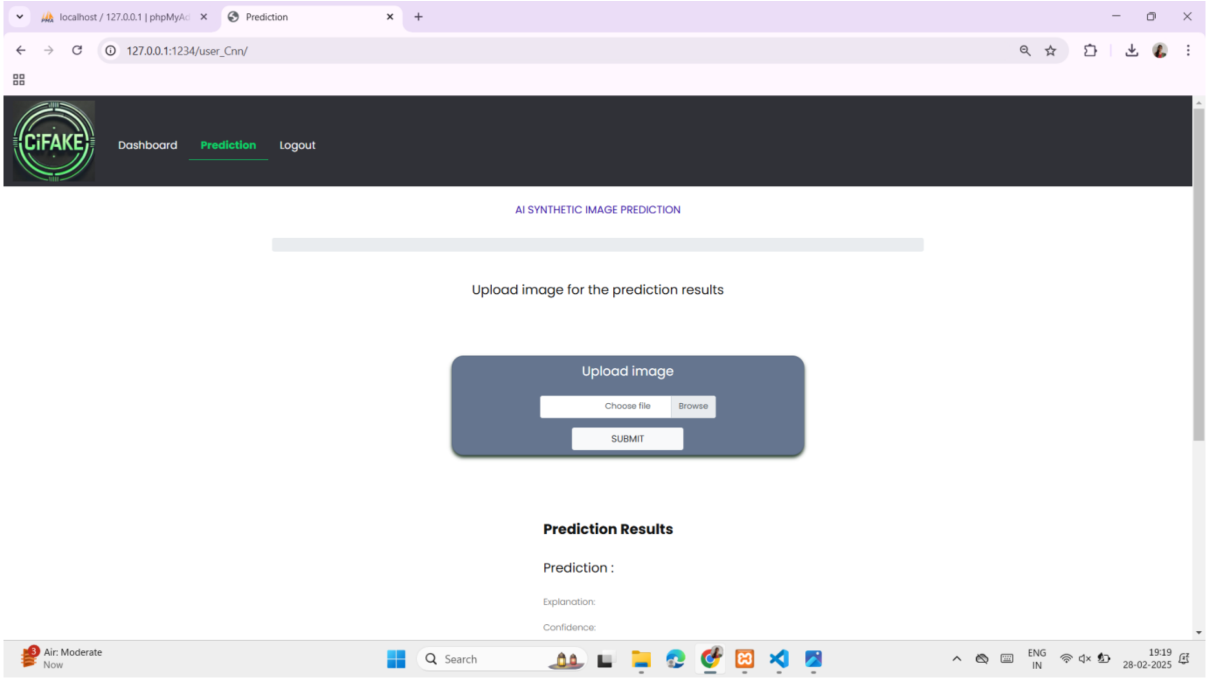
*Fig. 7.6 CNN Model*



WELCOME USER DASHBOARD

Welcome to our dashboard! Explore cutting-edge advancements in AI-generated image detection using a Convolutional Neural Network (CNN) trained on the CIFAKE dataset, a synthetic dataset mirroring CIFAR-10 images. This model identifies subtle visual imperfections in backgrounds rather than the main subject to classify images as real or AI-generated. With advancements in synthetic data generation, AI can now produce highly photorealistic details, such as reflections in water, making detection more challenging. To enhance transparency, Explainable AI techniques reveal key features influencing classification. The CIFAKE dataset is publicly available, supporting further research in AI image authentication. Stay updated with the latest insights and innovations!

*Fig. 7.7 User Dashboard*



AI SYNTHETIC IMAGE PREDICTION

Upload image for the prediction results

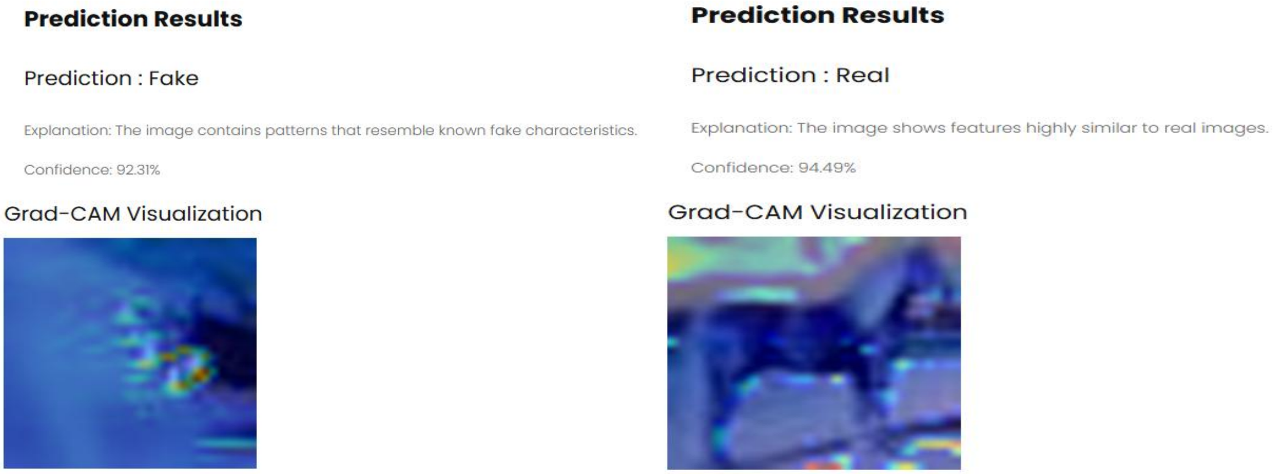
Prediction Results

Prediction :

Explanation:

Confidence:

*Fig. 7.8 Prediction Page*



Prediction Results

Prediction : Fake

Explanation: The image contains patterns that resemble known fake characteristics.

Confidence: 92.31%

Grad-CAM Visualization

Prediction Results

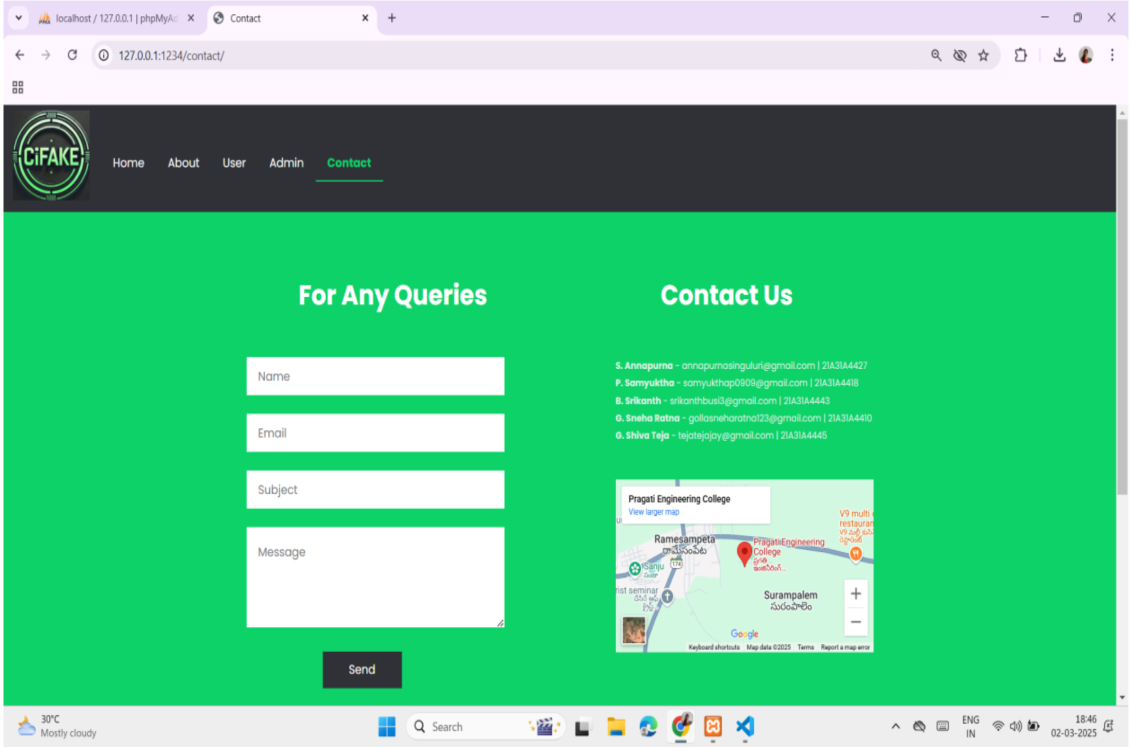
Prediction : Real

Explanation: The image shows features highly similar to real images.

Confidence: 94.49%

Grad-CAM Visualization

*Fig. 7.9 Prediction Result (Real or Fake)*



For Any Queries

Contact Us

**S. Annapurna** - annapurnasinguluri@gmail.com | 21A31A4427
**P. Samyuktha** - samyukthap0909@gmail.com | 21A31A4418
**B. Srikanth** - srikanthbusi3@gmail.com | 21A31A4443
**G. Sneha Ratna** - gollasneharatna123@gmail.com | 21A31A4410
**G. Shiva Teja** - tejatejajay@gmail.com | 21A31A4445

*Fig. 8.0 Contact Page*

# CHAPTER- 8

# CONCLUSION AND FUTURE WORK

# CONCLUSION AND FUTURE WORK

This project has proposed a method to improve our waning ability to recognize AI-generated images through the use of Computer Vision and to provide insight into predictions with visual cues. To achieve this, the project introduced the generation of a synthetic dataset using Latent Diffusion, recognition with Convolutional Neural Networks, and interpretation through Gradient Class Activation Mapping. The results showed that the synthetic images were of high quality and featured complex visual attributes, demonstrating that binary classification could effectively distinguish real and AI-generated images. Grad-CAM interpretation revealed interesting concepts within the images that were useful for predictions. In addition to the proposed method, a significant contribution is made through the release of the CIFAKE dataset, which contains a total of 120,000 images (60,000 real images from CIFAR-10 and 60,000 synthetic images generated for this project). This dataset provides the research community with a valuable resource for studying the social challenges posed by AI-generated imagery and significantly expands the available resources for developing and testing applied computer vision approaches. The reality of AI generating images that are indistinguishable from real-life photographs raises fundamental questions about the limits of human perception, and this project aimed to enhance that ability by leveraging AI itself. The proposed approach addresses the challenges of ensuring the authenticity and trustworthiness of visual data. Future work could involve exploring alternative techniques to classify the dataset, such as attention based models, which offer a promising direction for improving explainability in AI-based image recognition. Additionally, as synthetic imagery continues to evolve, it will be essential to update the dataset with images generated using advanced methods. Expanding the dataset to include images from other domains, such as human faces and clinical scans, could further enhance its applicability to various research fields. Ultimately, this project contributes to the on-going discourse on AI generated images, supporting the need for reliable authentication techniques. The public release of the CIFAKE dataset provides a valuable resource for interdisciplinary research, enabling further advancements in AI-driven image analysis and data trustworthiness.

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# APPENDIX – A

# SOURCE CODE

# SOURCE CODE

## User - Views.py

```
from django.shortcuts import render
from django.contrib import messages

def udashboard(request):
return render(request,'user/udashboard.html')

# Create your views here.
import matplotlib.pyplot as plt
import os
import numpy as np
import tensorflow as tf
import cv2
from django.shortcuts import render
from django.core.files.storage import FileSystemStorage
from django.conf import settings
from keras.models import load_model
IMG_SIZE = 32 # Set the image size (32x32)

def apply_gradcam(model, image_array):
grad_model = tf.keras.models.Model(

inputs=model.input,
outputs=[model.get_layer('conv2d_6').output, model.output]
)

with tf.GradientTape() as tape:
conv_outputs, predictions = grad_model(image_array)
```

```
loss = predictions[:, np.argmax(predictions[0])]
grads = tape.gradient(loss, conv_outputs)
pooled_grads = tf.reduce_mean(grads, axis=(0, 1, 2))
heatmap = tf.reduce_mean(tf.multiply(pooled_grads, conv_outputs), axis=-1)
heatmap = np.maximum(heatmap[0], 0) / np.max(heatmap[0]) # Normalize
heatmap = cv2.resize(heatmap, (IMG_SIZE, IMG_SIZE))
heatmap = np.uint8(255 * heatmap) # Convert to uint8
heatmap = cv2.applyColorMap(heatmap, cv2.COLORMAP_JET) # Apply colormap
return heatmap

def user_Cnn(request):
if request.method == 'POST' and 'data_file' in request.FILES:
uploaded_image = request.FILES['data_file']
fs = FileSystemStorage()
relative_path = fs.save(uploaded_image.name, uploaded_image)
file_path = os.path.join(settings.MEDIA_ROOT, relative_path) # Get the absolute file path

# Preprocess the image (resize to 32x32 and normalize)
image = tf.keras.preprocessing.image.load_img(file_path, target_size=(32, 32))
image_array = tf.keras.preprocessing.image.img_to_array(image)
image_array = image_array / 255.0 # Normalize the image
image_array = np.expand_dims(image_array, axis=0) # Add batch dimension
def predict_single_image(model, image_array):
prediction = model.predict(image_array)
predicted_class = np.argmax(prediction, axis=-1)[0]

label = 'Real' if predicted_class == 0 else 'Fake'
confidence = np.max(prediction)
return label, confidence
```

```
model = load_model('image_classification2_model.h5')
if not model.built:
model.build(input_shape=(None, 32, 32, 3))
label, confidence = predict_single_image(model, image_array)
print(f"Prediction: {label} (Confidence: {confidence:.2f})")
explanation = (
"The image shows features highly similar to real images."
if label == "Real"
else "The image contains patterns that resemble known fake characteristics."
)

# Apply Grad-CAM
heatmap = apply_gradcam(model, image_array)
image_uint8 = (image_array[0] * 255).astype(np.uint8) # Convert to uint8
overlay = cv2.addWeighted(image_uint8, 0.6, heatmap, 0.4, 0) # Blend with original image
# gradcam_path = os.path.join(settings.MEDIA_ROOT, "gradcam.png")
gradcam_filename = "gradcam.png"
gradcam_path = os.path.join(settings.MEDIA_ROOT, gradcam_filename)
gradcam_url = settings.MEDIA_URL + gradcam_filename

# cv2.imwrite(gradcam_path, overlay)
# Resize Grad-CAM overlay to a larger size (e.g., 256x256 or 512x512)

gradcam_large = cv2.resize(overlay, (256, 256), interpolation=cv2.INTER_CUBIC)
# Save the resized Grad-CAM image
cv2.imwrite(gradcam_path, gradcam_large)
return render(request, 'user/CNN_prediction.html', {
'prediction': label,
'explanation': explanation,
'confidence': f"{confidence * 100:.2f}%",
'gradcam_image': gradcam_url
})

return render(request, 'user/CNN_prediction.html')
```

## CNN model

```
# Updated CNN Model Architecture
model = Sequential([
Conv2D(32, (3, 3), activation='relu', input_shape=(IMG_WIDTH, IMG_HEIGHT, 3)),
BatchNormalization(),
MaxPooling2D(pool_size=(2, 2)),
Dropout(0.25),
Conv2D(64, (3, 3), activation='relu'),
BatchNormalization(),
MaxPooling2D(pool_size=(2, 2)),
Dropout(0.25),
Conv2D(128, (3, 3), activation='relu'),
BatchNormalization(),
MaxPooling2D(pool_size=(2, 2)),
Dropout(0.25),
Flatten(),
Dense(128, activation='relu'),
BatchNormalization(),
Dropout(0.5),
Dense(1, activation='sigmoid')
])
# Compile the model with a lower learning rate
model.compile(optimizer=Adam(learning_rate=0.0001),loss='binary_crossentropy'
,metrics=['accuracy'])
```

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# CIFAKE: Precision Image Classification and Explainable AI for Detecting Synthetic Generations

**D. Chakra Satya Tulasi[1], Singuluri Annapurna[2], Pasumarthi Samyuktha[3], Busi Srikanth[4], Golla Sneha Ratna[5], Gampala Lakshmi Shiva Teja[6]**

Assistant Professor, Department of CSE (Data Science) In Pragati Engineering College, Surampalem, Andhra Pradesh, India,[1]
UG Students Department of CSE (Data Science) In Pragati Engineering College, Surampalem, Andhra Pradesh, India. [2,3,4,5,6]

**Abstract- The rapid advancements in synthetic data generation have resulted in AI-generated images that are nearly indistinguishable from real photographs, posing challenges in data authenticity and reliability. This study aims to enhance the detection of AI-generated images using computer vision techniques. A synthetic dataset resembling the ten classes of CIFAR-10 is created using latent diffusion, providing a direct comparison between real and AI-generated images. The classification task is framed as a binary problem, distinguishing real images from synthetic ones. To achieve this, a Convolutional Neural Network (CNN) is trained to classify the images with optimal performance. After fine-tuning hyperparameters and evaluating 36 distinct network architectures, the best-performing model achieves an accuracy of 92.98%. Additionally, explainable AI techniques, such as Gradient Class Activation Mapping, are applied to interpret the model's decision-making process. Interestingly, the analysis reveals that rather than focusing on primary subjects, the model relies on subtle background inconsistencies to differentiate real images from synthetic ones. To support further research in this domain, the newly generated dataset, CIFAKE, is made publicly available for future studies.**

**Keywords- AI-generated Images, Generative AI, Latent Diffusion**

## I. INTRODUCTION

In an era where artificial intelligence (AI) is reshaping the boundaries of creativity, the line between reality and illusion is becoming increasingly blurred. What was once the domain of human artistry and photography has now been infiltrated by AI-generated visuals so convincing that even the sharpest eyes struggle to differentiate between what is real and what is artificially created. This advancement has not only revolutionized digital art but also sparked serious concerns about authenticity, trust, and the ethical implications of synthetic imagery.

The rise of powerful generative models, such as Latent Diffusion Models (LDMs), has ushered in a new age of hyper-realistic image synthesis. Unlike earlier AI-generated images that were plagued with obvious artifacts and distortions, modern AI can now produce photorealistic visuals indistinguishable from those captured by cameras. These AI creations are no longer just experimental outputs; they have reached a level where they can compete with human-made content and even win prestigious art competitions. As this technology becomes more accessible, so do its potential risks—ranging from misinformation and fraud to deepfake scandals and privacy breaches.

At the heart of this transformation lies a crucial question: If AI can generate images that are virtually identical to real ones, how can we trust what we see? This dilemma is not just a technological challenge but also a philosophical one, raising fundamental concerns about perception, digital reality, and the reliability of human knowledge. Our traditional understanding of authenticity is under siege, and without robust detection mechanisms, we risk a future where fabricated visuals dictate narratives, manipulate public perception, and erode trust in digital media.

To address this growing challenge, this study leverages computer vision and deep learning to create a reliable method for distinguishing AI-generated images from real ones. By generating a synthetic dataset that mirrors real-world imagery, we train a classification model capable of detecting subtle differences imperceptible to the human eye. A key contribution of this research is the creation of CIFAKE, a novel dataset comprising 120,000 images—60,000 authentic images from the CIFAR-10 dataset and 60,000 AI-generated counterparts. This dataset serves as the foundation for training a convolutional neural network (CNN) to classify images as either real or synthetic.

Beyond classification, this study also incorporates Explainable AI (XAI) techniques, such as Gradient Class Activation Mapping, to uncover the features that AI models rely on when making their predictions. Interestingly, our findings reveal that rather than focusing on the primary subject of an image, the model identifies minute imperfections in the background—subtle clues that expose an image’s artificial origins.

As generative AI continues to advance, the ability to detect synthetic images will become an essential safeguard against misinformation and digital deception. This research takes a step toward that goal, offering both a powerful detection framework and deeper insights into the evolving landscape of AI-generated imagery.
The remainder of this paper is structured as follows: Section II explores the state-of-the-art research in AI-generated image detection, Section III details the methodology for dataset generation and model training, Section IV presents experimental results and analysis, and Section V discusses future directions and potential enhancements for improving AI-generated image detection systems.

## II. LITERATURE REVIEW

The ability of artificial intelligence to generate hyper-realistic images has ushered in a new era where the lines between reality and fabrication have become increasingly blurred. Advanced generative models such as Latent Diffusion Models (LDMs)—including Stable Diffusion, DALL-E, and Imagen—have revolutionized image synthesis, producing visuals so convincing that even trained human observers struggle to differentiate them from real-world photographs. While this progress fuels artistic innovation and technological advancements, it also presents a formidable challenge: how do we reliably detect synthetic images in an era where deception has never been easier?

To tackle this, researchers have developed a range of detection techniques. Some rely on digital forensics, such as DE-FAKE, which leverages digital fingerprints and frequency analysis to uncover telltale signs of AI manipulation. Others turn to deep learning, with architectures like Efficient Net and Vision Transformers demonstrating remarkable accuracy in classifying synthetic images, especially when trained on datasets like the Deep Fake Detection Challenge. Meanwhile, temporal analysis approaches—such as CNN-LSTM and RNNs—explore motion patterns and frame inconsistencies in videos, helping expose manipulations that static image detection might miss. Despite these strides, the rapid improvement of generative models continues to outpace detection capabilities, underscoring the need for automated, adaptable solutions.

One key development in this space is the integration of Explainable AI (XAI) to enhance transparency in AI-driven classification. Techniques such as Grad-CAM have been instrumental in shedding light on the decision-making process of deep learning models, revealing which visual features contribute to a classification outcome. In support of further research, this study introduces the CIFAKE dataset—a synthetic dataset designed to aid in distinguishing real and AI-generated images, adding a crucial resource to the field. Yet, challenges persist. Issues of scalability, model generalization, and adversarial robustness remain open problems, necessitating continued innovation in detection methodologies.

Beyond image authenticity, machine learning has also been making waves in biomedical research, particularly in predicting adverse drug reactions. Zhou et al. [9] devised a model that integrates molecular structures, biological interactions, and pathway analysis to forecast potential drug side effects before clinical trials—a breakthrough that could significantly enhance patient safety and pharmaceutical efficacy.

In another domain, the intersection of machine learning and bioinformatics has yielded transformative insights into disease mechanisms. Kumar et al. [10] applied AI-driven analysis to genomic and proteomic data, uncovering previously unknown biomarkers for early cancer detection and targeted treatment. Their work highlights the growing potential of AI in precision medicine, where early intervention can be life-saving.

Despite these remarkable advancements, significant challenges remain. Algorithmic bias, data integrity, and explainability are key concerns in AI-driven healthcare applications. Nguyen et al. [11] emphasize the necessity of interpretable models, ensuring that AI's decision-making processes are transparent and trustworthy for clinicians and researchers alike.

Beyond the technical challenges, ethical considerations surrounding AI in healthcare and security demand urgent attention. Morales et al. [12][13] call for a structured ethical framework that balances AI’s potential with responsible usage, ensuring that these powerful tools are deployed for the benefit of society rather than manipulation or harm. Regulatory frameworks and ethical oversight must evolve alongside AI’s rapid advancements to safeguard its integrity in critical applications.

As the digital and biological landscapes continue to intertwine with AI, the importance of robust, transparent, and ethical AI-driven methodologies cannot be overstated. Whether in detecting synthetic imagery or predicting life-altering medical outcomes, the road ahead requires a synthesis of technological innovation, ethical responsibility, and scientific rigor.

## III. SYSTEM ANALYSIS

### Existing Systems

The detection of AI-generated images has evolved significantly with the emergence of sophisticated generative models. Latent Diffusion Models (LDMs), including Stable Diffusion, DALL-E, and Imagen, are capable of producing highly realistic images with intricate details such as reflections, motion blur, and depth of field. While these advancements enhance synthetic image generation, they also introduce significant challenges for detection methodologies.

To address this, various approaches have been proposed. The DE-FAKE method utilizes digital fingerprint analysis and Fourier transforms to differentiate real and synthetic images. Deep learning-based models, such as EfficientNet and Vision Transformers, have shown competitive results in detecting AI-generated content, achieving high F1 scores and AUC values when tested on benchmark datasets like the DeepFake Detection Challenge. Additionally, Optical Flow Techniques have been applied to analyze motion inconsistencies in AI-generated faces, providing moderate detection accuracy. Hybrid models, such as CNN-LSTM architectures, integrate spatial and temporal features, enhancing the detection of deepfake videos by capturing frame-by-frame inconsistencies.

Although these techniques offer promising results, they come with inherent limitations.

### Limitations

- **Effectiveness Against High-**Fidelity Synthetic Images – Many existing detection systems rely on the presence of visual artifacts or distortions that were once common in early generative models. However, as AI-generated images become increasingly flawless, these detectable glitches are becoming scarce, reducing the effectiveness of traditional detection methods.
- **Limited Generalization –** Most current techniques are optimized for specific datasets, such as those containing human faces. Their adaptability to a wider range of image types, including medical scans and other specialized domains, remains limited, impacting their applicability across diverse real-world scenarios.
- **Lack of Interpretability –** Many AI-based detection models function as "black boxes," offering little insight into their decision-making process. This lack of transparency diminishes their reliability in critical applications, such as fraud detection and forensic analysis, where understanding the reasoning behind a classification is essential.
- **Overlooking Subtle Visual Cues –** While detection models perform well on identifying obvious artifacts, they often struggle to recognize more nuanced indicators of synthetic imagery, such as minute pixel inconsistencies or unnatural background textures that can serve as subtle but crucial clues in distinguishing AI-generated content from real photographs.
- **Accuracy Challenges –** Techniques like DE-FAKE and Optical Flow Analysis, while innovative, still fall short of human-level perception, particularly when dealing with advanced generative models that produce nearly imperceptible synthetic images. As AI-generated content becomes increasingly indistinguishable from real-world visuals, existing detection approaches must evolve to maintain their effectiveness.

Given these challenges, the ongoing development of detection methods must focus on improving adaptability, enhancing interpretability, and refining techniques to detect even the most imperceptible markers of AI synthesis.

### Proposed System

To effectively distinguish between real and AI-generated images, the proposed system leverages a powerful Convolutional Neural Network (CNN) designed for robust image classification. Through meticulous hyperparameter tuning, the model achieves a remarkable accuracy of 92.98%, surpassing existing detection methods. The CNN architecture employs convolutional layers to extract critical features and fully connected layers to make precise classifications, ensuring high reliability in differentiating synthetic images from authentic ones.

To enhance the system’s interpretability, the model integrates Gradient Class Activation Mapping (Grad-CAM), a widely used Explainable AI (XAI) technique. Grad-CAM produces heatmaps that visually highlight the specific areas of an image that contribute most to the model’s decision. This feature enhances transparency, fosters user trust, and provides meaningful insights into how the system identifies AI-generated content.

A significant contribution of this study is the introduction of CIFAKE, a novel dataset consisting of 120,000 images. It includes 60,000 real images from the well-established CIFAR-10 dataset and 60,000 synthetic images generated using Stable Diffusion. This dataset is designed to be diverse and representative of real-world conditions, ensuring the model is well-equipped to handle various image complexities.

Additionally, the system employs a dynamic retraining mechanism to maintain its effectiveness against advancements in generative models. By continuously updating its dataset with newly generated and real images, the model remains resilient to emerging synthetic image features, preventing performance degradation over time.

Another key aspect of the system is its ability to detect subtle visual irregularities—such as imperceptible artifacts and background inconsistencies—often overlooked by traditional methods. This capability significantly enhances detection accuracy, making the system a robust solution against high-quality AI-generated images. By integrating cutting-edge classification techniques, adaptability through retraining, and explainability via Grad-CAM, this approach offers a comprehensive and future-proof method for synthetic image detection.

**Advantages of the Proposed System**

- **Superior Classification Accuracy –** The CNN model achieves an impressive accuracy rate of 92.98%, significantly outperforming traditional detection techniques like DE-FAKE and Optical Flow Analysis, which struggle with detecting highly realistic synthetic images.
- **Enhanced Interpretability** – Unlike black-box models such as Vision Transformers and EfficientNet, this system utilizes Grad-CAM, enabling users to visualize which image regions influenced the classification decision. This feature adds a layer of transparency and improves trust in AI-based detection.
- **Adaptive Learning Mechanism –** Unlike static models that degrade in performance as generative techniques evolve, the proposed system incorporates dynamic retraining, ensuring continued adaptability to newly emerging synthetic image features.
- **High-Quality Dataset –** The CIFAKE dataset, specifically curated for this research, offers a balanced mix of real and AI-generated images. This dataset provides greater diversity and scalability compared to existing resources, making it an invaluable asset for synthetic image detection.
- **Detection of Subtle Anomalies –** Leveraging Grad-CAM, the system can identify minute visual inconsistencies, such as slight pixel distortions and unnatural texture patterns, which are often undetectable to the human eye.
- **Versatile Applications –** Unlike many existing systems that focus solely on specific use cases like deepfake detection, this approach is adaptable across various fields, including medical imaging, forensic analysis, and digital security.
- **Scalability and Efficiency –** Designed to process vast amounts of data efficiently, this system can scale to handle large datasets, making it suitable for industries that require extensive image authentication, such as pharmaceutical research, media forensics, and cybersecurity.
- **Advancement in Personalized Medicine and Drug Safety –** By leveraging AI's capability to detect subtle patterns in medical imaging and genomic data, this approach can contribute to personalized healthcare solutions, optimizing treatments based on an individual's health profile and ensuring enhanced drug efficacy and patient safety.

Through this highly accurate, explainable, and adaptive system, the study provides a robust solution to the growing challenge of detecting AI-generated images, addressing both technical limitations and ethical concerns in an increasingly synthetic digital landscape.

**System Design**

**System Architecture**

Below diagram depicts the whole system architecture.

**System Implementation**

**Modules**

The system is structured into distinct modules that work together to ensure the accurate classification of real and AI-generated images. These modules cover dataset preparation, model training, adaptive learning, anomaly detection, and user interaction.

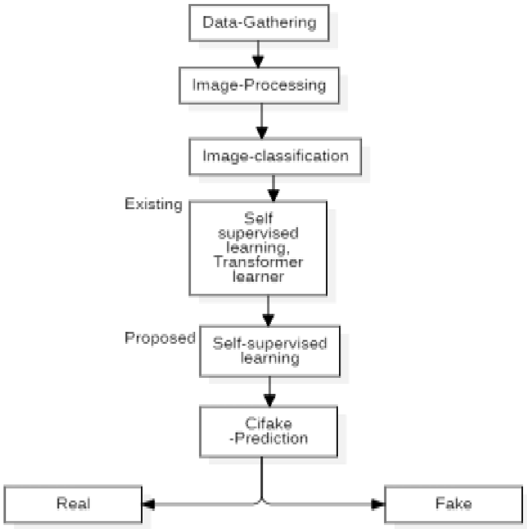


Fig 1. Methodology followed for proposed model

### Data Preparation and Augmentation

To develop a reliable dataset, 60,000 authentic images are sourced from CIFAR-10, while 60,000 synthetic images are generated using Stable Diffusion, a state-of-the-art Latent Diffusion Model (LDM).

To maintain a standardized input format, all images are resized to 32×32 pixels using bilinear interpolation. Each image is assigned a class label:

- **REAL –** Represents genuine images from CIFAR-10
- **FAKE –** Represents AI-generated images

To enhance the model's ability to generalize, data augmentation techniques are applied

- **Flipping –** Introduces variations in image orientation
- **Rotation and Scaling –** Simulates real-world distortions
- **Noise Injection –** Helps the model distinguish fine-grained artifacts

By implementing these preprocessing strategies, the dataset becomes more diverse and resilient, improving classification accuracy.

### Model Training and Optimization

The system utilizes a Convolutional Neural Network (CNN) for binary classification. The architecture consists of multiple convolutional layers with filter sizes {16, 32, 64, 128}, followed by pooling layers and fully connected layers.

To achieve the best performance, hyperparameter tuning is conducted across 36 configurations, fine-tuning key parameters such as:

- Learning rate
- Batch size
- Number of layers and filter sizes

The model is trained using the binary cross-entropy loss function, optimized through backpropagation with the Adam optimizer, ensuring efficient gradient updates. The optimized CNN achieves a classification accuracy of 92.98%, demonstrating its robustness against high-fidelity synthetic images.

### Adaptive Learning via Dynamic Retraining

To keep pace with evolving generative AI techniques, the system implements a dynamic retraining mechanism. This enables continuous improvement by periodically incorporating new real and synthetic images into the dataset, especially those generated by emerging deep learning models.

By refreshing the dataset and retraining the model at intervals, the system remains adaptable and effective in detecting advanced synthetic images with greater precision.

### Anomaly Identification with Explainable AI

The system integrates Gradient Class Activation Mapping (Grad-CAM), an Explainable AI (XAI) technique, to highlight regions in an image that significantly influence classification decisions.

For AI-generated images, the model often detects subtle visual artifacts, such as:

- Inconsistencies in texture
- Background anomalies
- Unnatural lighting or edges

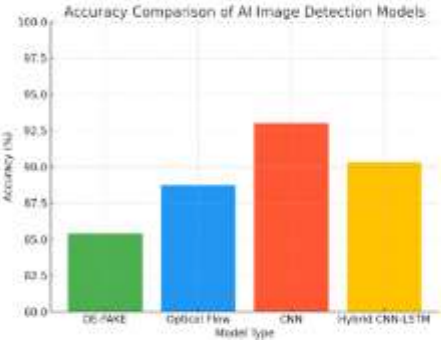
These highlighted regions allow for greater interpretability, making it easier to understand why an image is classified as real or synthetic.

**Interactive User Interface and Reporting**
A user-friendly interface is designed to make the system accessible and insightful for users. Key features include:

- **Classification Dashboard –** Displays whether an image is real or synthetic
- **Heatmaps from Grad-CAM –** Provides a visual explanation of model predictions
- **Performance Metrics –** Showcases accuracy, precision, recall, and F1-score
- **Custom Image Upload –** Allows users to test the system with new images

By incorporating transparency and interactivity, this interface ensures trust and usability, making AI-generated image detection more interpretable and efficient.

## IV. RESULTS AND DISCUSSION



In above diagram a discribes about verious algorithmic accuracy comparion graph

CNN Model

[illegible]

| accuracy | precision | recall | f1 |
|---|---|---|---|
| [illegible] | [illegible] | [illegible] | [illegible] |

## V. CONCLUSION

This study introduced a novel approach to enhancing human ability to distinguish between AI-generated and real images by leveraging computer vision techniques. By integrating synthetic dataset generation using Latent Diffusion, classification via Convolutional Neural Networks, and interpretability through Gradient Class Activation Mapping (Grad-CAM), the research aimed to improve both detection accuracy and explainability. The findings demonstrated that the synthetic images exhibited intricate visual characteristics, and the binary classification model achieved an impressive accuracy of 92.98%. Additionally, Grad-CAM provided insightful visual justifications for model predictions, highlighting key image regions that influenced classification.

A major contribution of this study is the CIFAKE dataset, a comprehensive dataset comprising 120,000 images, including 60,000 real images from CIFAR-10 and 60,000 AI-generated images produced specifically for this research. This dataset serves as a crucial asset for the academic community, offering new opportunities to develop and refine computer vision-based solutions for identifying AI-generated content. As synthetic images become increasingly indistinguishable from real ones, this research addresses critical concerns regarding the authenticity and reliability of digital imagery, underscoring the need for continued advancements in AI-driven detection techniques.

For future exploration, alternative classification approaches can be investigated to further enhance performance. Attention-based mechanisms, such as Transformer-based architectures, present a promising avenue for improving classification accuracy while enhancing explainability. Moreover, as AI-generated images continue to evolve in realism and complexity, updating the dataset with more advanced synthetic images will be essential to maintaining detection efficacy. Expanding the dataset beyond CIFAR-10, incorporating domains such as facial imagery, medical scans, or artistic renderings, could further extend the applicability of this approach to various fields, including cybersecurity, healthcare, and digital forensics.

In conclusion, this study not only proposes an effective system for detecting AI-generated images but also contributes a valuable dataset and an interpretable framework that fosters trust in AI-driven decision-making. By making the CIFAKE dataset publicly available, this work paves the way for interdisciplinary research aimed at addressing the growing challenges posed by AI-generated content and its impact on digital authenticity.

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