

ABSTRACT

This project focuses on the development of an image-based CAPTCHA recognition system using deep learning models to detect and classify CAPTCHA characters. The system employs Convolutional Neural Networks (CNN) architectures, both of which are efficient in handling image classification tasks. The dataset for the project is sourced from Kaggle, containing various CAPTCHA images that mimic real-world scenarios. The CNN model is leveraged for feature extraction and character recognition, while, known for its lightweight structure and high accuracy, is used for enhancing the model's performance, particularly on mobile devices. The backend of the system is developed using Python, while the frontend is created using HTML, CSS, and JavaScript to provide an interactive interface for uploading CAPTCHA images. Once an image is uploaded, the model will accurately detect the individual characters in the CAPTCHA. This project demonstrates a powerful and efficient approach to CAPTCHA recognition, suitable for automation tasks.

Keywords: CAPTCHA recognition, deep learning, CNN, image classification, Python, HTML, CSS, JavaScript, character detection.

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CHAPTER 1 – INTRODUCTION

In the digital era, as automation and artificial intelligence continue to evolve, the need for effective web security mechanisms has never been more critical. One of the most widely adopted methods of distinguishing between human users and automated bots is the CAPTCHA—an acronym for Completely Automated Public Turing test to tell Computers and Humans Apart. CAPTCHAs serve as gatekeepers for web forms, login portals, ticketing systems, and various online services, preventing bots from engaging in harmful activities such as brute-force attacks, spamming, credential stuffing, and data scraping. However, while CAPTCHAs have proved to be a relatively robust security solution, they come with their own set of challenges, particularly in terms of usability and accessibility.

CAPTCHAs often require users to interpret distorted, noisy, and sometimes ambiguous text, solve puzzles, or identify objects in complex images. While these methods are effective in thwarting automated bots, they can also alienate legitimate human users—especially those with visual impairments, cognitive disabilities, or low digital literacy. This poses significant usability issues and may lead to user frustration, failed interactions, and even abandonment of online services. Consequently, there's a growing demand to either enhance CAPTCHA accessibility or develop intelligent systems that can interpret and solve CAPTCHAs efficiently, thus helping improve web accessibility and automated testing workflows.

This project takes a forward-looking approach by introducing a CAPTCHA recognition system based on deep learning, focusing on the accurate detection and classification of characters within CAPTCHA images. The system leverages the power of Convolutional Neural Networks (CNNs)—a category of deep neural networks highly effective in image recognition and classification tasks. CNNs have demonstrated remarkable capabilities in computer vision domains, such as handwritten digit recognition, face detection, and object identification, due to their ability to automatically learn and extract hierarchical visual features.

CHAPTER 2 – SYSTEM ANALYSIS

a. Existing System

CAPTCHAs have long been a fundamental web security mechanism to differentiate humans from automated bots. They work on the assumption that humans can easily interpret distorted or obfuscated images, while machines cannot. Traditional CAPTCHAs include distorted text, image selections (such as identifying traffic lights or buses), or simple puzzles. While these methods have proven effective at stopping basic bots, they are not without flaws, especially when it comes to human usability and accessibility.

Disadvantages

- **Limited accuracy:** Human errors can lead to missed detections, especially in crowded or fast-moving scenes.
- **Delayed response:** The human eye and attention span are limited, making it difficult for operators to constantly monitor the footage and respond immediately to a detected threat.
- **Labor-intensive:** Continuous monitoring requires significant human resources, especially in high-risk or high-traffic areas, leading to higher operational costs.
- **Lack of real-time alerts:** In many existing systems, there is no mechanism to trigger real-time alerts, meaning that security personnel must rely on reviewing recorded footage, which is time-consuming and reactive.

b. proposed System

The **proposed CAPTCHA recognition system** overcomes the limitations of existing methods by using **deep learning**, specifically **Convolutional Neural Networks (CNNs)** and **MobileNet**, to automatically identify characters from a wide variety of CAPTCHA images. This system not only enhances recognition accuracy but also improves accessibility and usability for end users. It is built to function in real time and to handle modern, complex CAPTCHA variations.

The system is designed with a modular architecture consisting of:

- A **frontend** (HTML, CSS, JavaScript) where users can upload CAPTCHA images.
- A **backend** (Python with TensorFlow/PyTorch) that processes the image, segments characters, and classifies them using trained CNN models.
- An **output interface** that displays the decoded CAPTCHA text in a user-friendly manner.

CHAPTER 3 – FEASIBILITY STUDY

a. Technical Feasibility

The proposed CAPTCHA recognition system is technically feasible as it utilizes well-established technologies such as Python for backend processing and CNN-based deep learning models for accurate image classification. The project leverages TensorFlow/Keras, which are open-source and widely supported libraries for training and deploying neural networks. Additionally, the frontend is built using standard web technologies—HTML, CSS, and JavaScript—which ensures platform independence and responsiveness. Since the dataset is available on Kaggle, no extensive data collection is required. The project can be developed and tested using commonly available hardware (with GPU support for faster training), making it technically viable and scalable.

b. Operational Feasibility

Operational feasibility is confirmed by the practicality and ease of using the CAPTCHA recognition system. The intuitive user interface allows non-technical users to upload CAPTCHA images and view recognized characters effortlessly. The backend processes run automatically upon image submission, reducing manual intervention and improving efficiency. The model's accuracy ensures reliable outputs, which is crucial for real-time applications such as automated form submissions or bot detection systems. Integration with existing platforms can be achieved with minimal modifications, and the modular design allows for easy maintenance and upgrades. Hence, the system is user-friendly, reliable, and aligns with operational workflows effectively.

c. Economic Feasibility

The economic feasibility of this project is strong, considering its low development and maintenance cost. Most of the tools and frameworks used—such as Python, TensorFlow, and front-end web technologies—are open-source, reducing licensing expenses. The dataset is publicly available on Kaggle, which eliminates data procurement costs. Initial infrastructure

can rely on local machines or free cloud-tier platforms, while further scalability can be achieved through low-cost cloud services. The automation of CAPTCHA solving can lead to long-term savings in manual labor, and the model's reusability across various applications provides good return on investment (ROI), making the system economically sustainable.

CHAPTER 4 – SYSTEM REQUIREMENT SPECIFICATION DOCUMENT

a. Overview

The image-based CAPTCHA recognition system aims to automate the process of interpreting and decoding CAPTCHA images using deep learning techniques, primarily Convolutional Neural Networks (CNNs). CAPTCHAs (Completely Automated Public Turing test to tell Computers and Humans Apart) are used widely to differentiate between genuine users and bots. However, in scenarios where automated access is required, CAPTCHA solving can be a bottleneck. This system provides a solution by using deep learning models to effectively detect and classify characters embedded in CAPTCHA images. The project employs a pre-trained CNN model to extract image features and recognize alphanumeric patterns. Additionally, a lightweight model is optionally integrated to enhance performance on resource-constrained devices, such as mobile phones.

The backend is developed using Python and Flask, integrating machine learning workflows for prediction. The frontend utilizes HTML, CSS, and JavaScript to offer a seamless user interface where users can upload CAPTCHA images and view real-time results. The dataset used for training is sourced from Kaggle, consisting of diverse and challenging CAPTCHA images that closely replicate those found in real-world environments. This system not only showcases the utility of CNNs in image-based tasks but also provides a practical tool for CAPTCHA automation, making it suitable for applications in data scraping, testing environments, and accessibility tools.

b. Module Description

The system is divided into several functional modules:

1. Data Acquisition Module

- **Purpose:** Ingests CAPTCHA image datasets for training and real-time input.

- **Input:** JPEG/PNG images of distorted text (CAPTCHAs).
- **Output:** Image dataset loaded for preprocessing.

2. Preprocessing Module

- **Purpose:** Enhances CAPTCHA image quality for optimal CNN input.
- **Techniques:** Grayscale conversion, resizing, thresholding, noise removal.
- **Output:** Normalized and cleaned images.

3. Character Segmentation and Labeling Module (Optional)

- **Purpose:** If needed, isolates individual characters for training.
- **Methods:** Contour detection, bounding box extraction.
- **Output:** Cropped character images and associated labels.

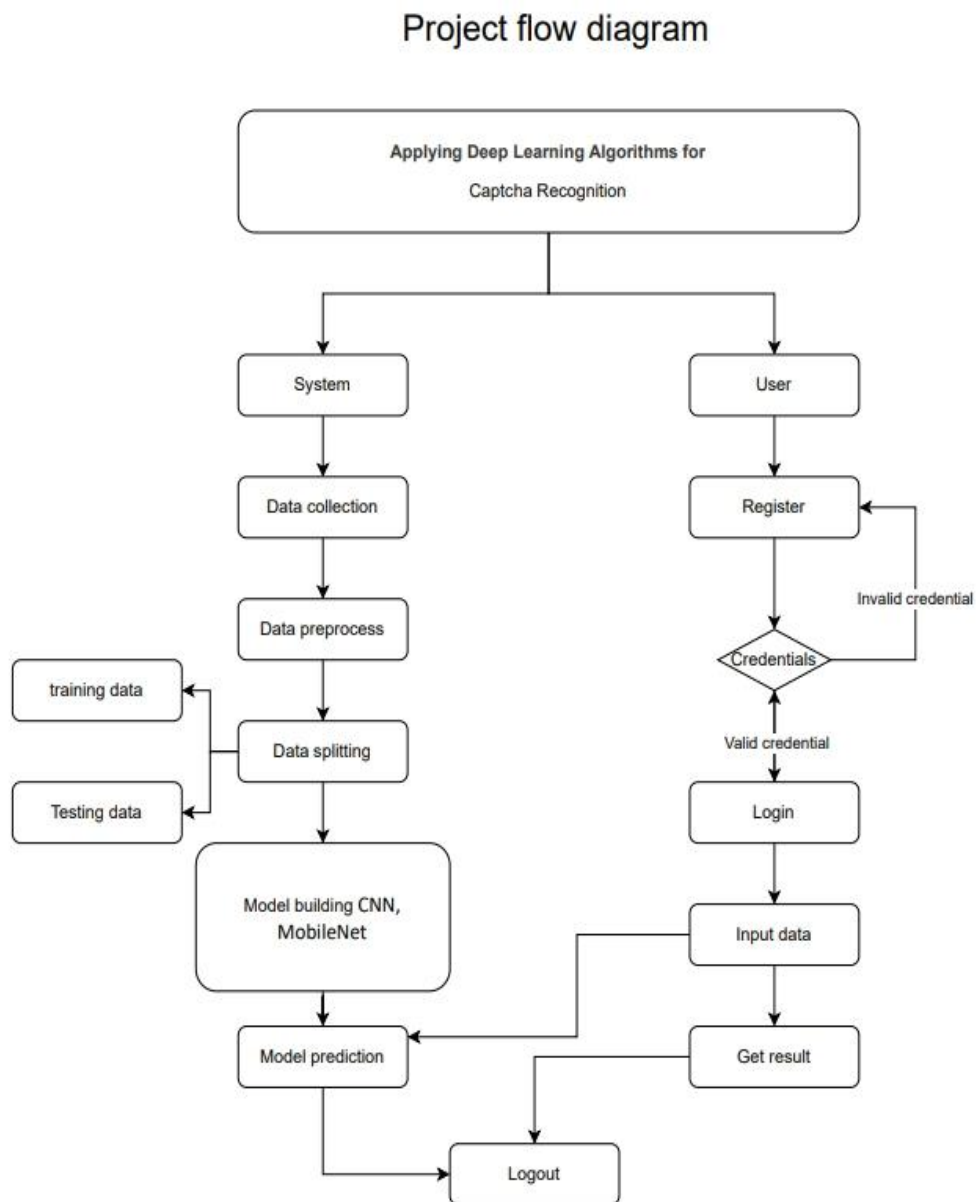
4. Model Training and Prediction Module

- **Purpose:** Trains a CNN model to learn and classify alphanumeric characters.
- **Functions:**
 - Train model on labeled dataset (characters A-Z, 0-9).
 - Use trained model to predict characters in uploaded CAPTCHA images.
- **Output:** Decoded string (e.g., "X7YDZ") with confidence scores.

5. Evaluation and Report Generation Module

- **Purpose:** Evaluates the trained model and provides decoding logs.
- **Metrics:** Accuracy, loss, character-wise precision/recall.
- **Output:** Visualization plots (loss/accuracy curves), prediction logs.

c. Process Flow



d. SDLC Methodology

SOFTWARE DEVELOPMENT LIFE CYCLE

The meaning of Agile is swift or versatile. "Agile process model" refers to a software development approach based on iterative development. Agile methods break tasks into smaller iterations, or parts do not directly involve long term planning. The project scope and requirements are laid down at the beginning of the development process. Plans regarding the number of iterations, the duration and the scope of each iteration are clearly defined in advance. Each iteration is considered as a short time "frame" in the Agile process model, which typically lasts from one to four weeks. The division of the entire project into smaller parts helps to minimize the project risk and to reduce the overall project delivery time requirements. Each iteration involves a team working through a full software development life cycle including planning, requirements analysis, design, coding, and testing before a working product is demonstrated to the client.

Actually, Agile model refers to a group of development processes. These processes share some basic characteristics but do have certain subtle differences among themselves. A few Agile SDLC models are given below: Crystal A tern Feature-driven development Scrum Extreme programming (XP) Lean development Unified process In the Agile model, the requirements are decomposed into many small parts that can be incrementally developed.

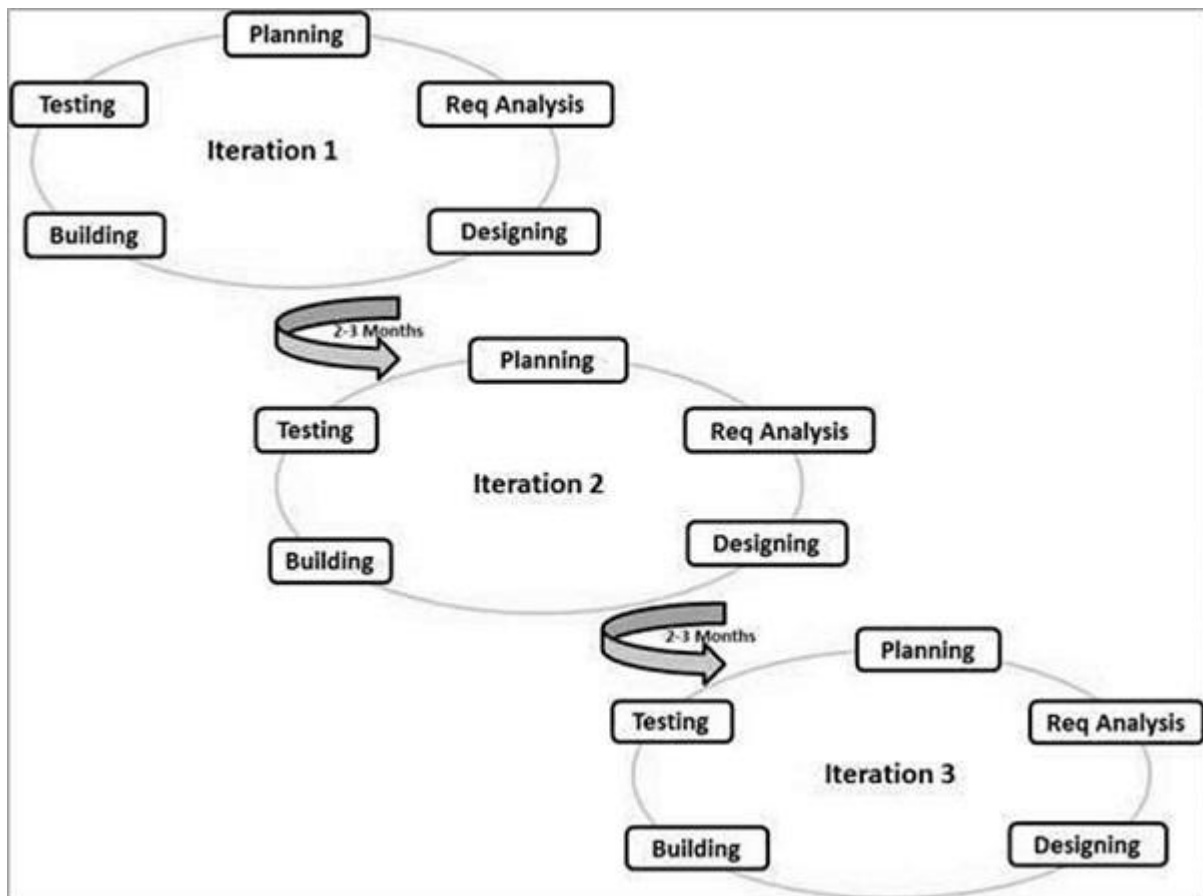
The Agile model adopts Iterative development. Each incremental part is developed over an iteration. Each iteration is intended to be small and easily manageable and that can be completed within a couple of weeks only. At a time one iteration is planned, developed and deployed to the customers. Long-term plans are not made.

Agile model is the combination of iterative and incremental process models. Steps involve in agile SDLC models are:

- Requirement gathering
- Requirement Analysis
- Design Coding
- Unit testing

- Acceptance testing

The time to complete an iteration is known as a Time Box. Time-box refers to the maximum amount of time needed to deliver an iteration to customers. So, the end date for an iteration does not change. Though the development team can decide to reduce the delivered functionality during a Time-box if necessary to deliver it on time. The central principle of the Agile model is the delivery of an increment to the customer after each Time-box.



Principles of Agile model:

- To establish close contact with the customer during development and to gain a clear understanding of various requirements, each Agile project usually includes a customer representative on the team. At the end of each iteration stakeholders and the customer representative review, the progress made and re-evaluate the requirements.

- Agile model relies on working software deployment rather than comprehensive documentation.
- Frequent delivery of incremental versions of the software to the customer representative in intervals of few weeks.
- Requirement change requests from the customer are encouraged and efficiently incorporated.

Advantages:

- Working through Pair programming produces well written compact programs which has fewer errors as compared to programmers working alone.
- It reduces total development time of the whole project. Customer representatives get the idea of updated software products after each iteration. So, it is easy for him to change any requirement if needed.

Disadvantages:

- Due to lack of formal documents, it creates confusion and important decisions taken during different phases can be misinterpreted at any time by different team members.
- Due to the absence of proper documentation, when the project completes and the developers are assigned to another project, maintenance of the developed project can become a problem.

SOFTWARE DEVELOPMENT LIFE CYCLE – SDLC:

In our project we use waterfall model as our software development cycle because of its step-by-step procedure while implementing.

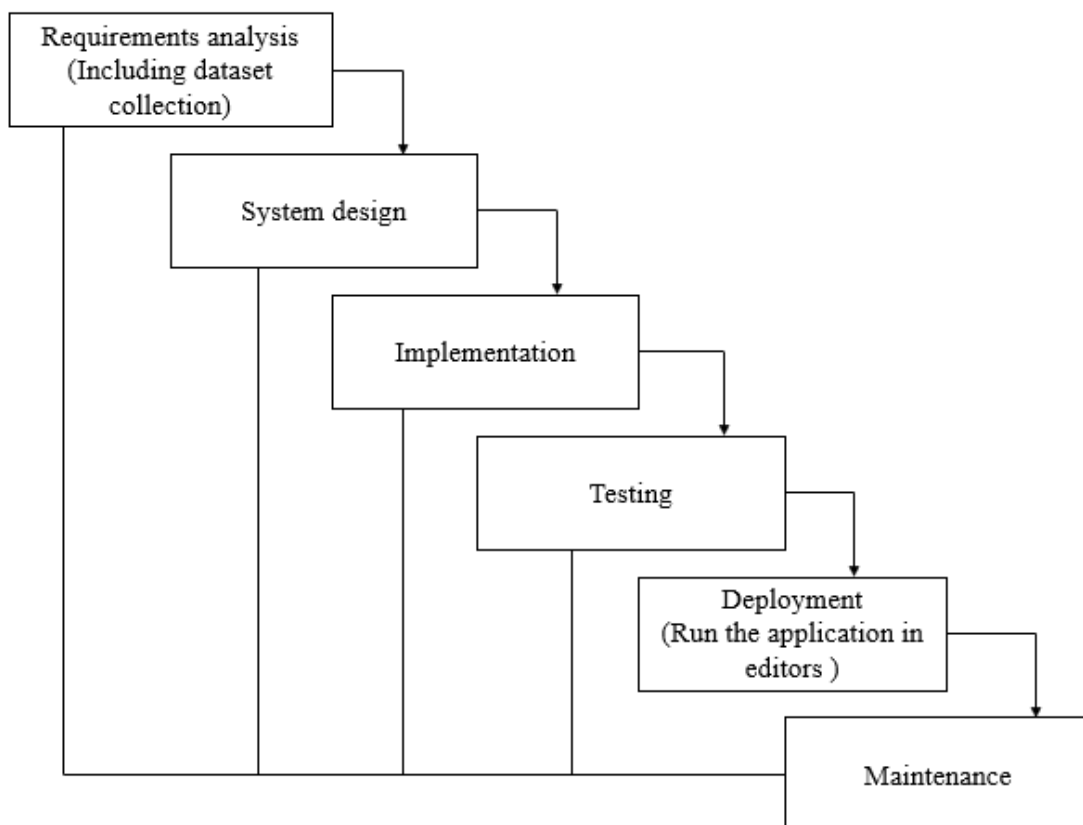


Fig1: Waterfall Model

- **Requirement Gathering and analysis** – All possible requirements of the system to be developed are captured in this phase and documented in a requirement specification document.
- **System Design** – The requirement specifications from first phase are studied in this phase and the system design is prepared. This system design helps in specifying hardware and system requirements and helps in defining the overall system architecture.
- **Implementation** – With inputs from the system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality, which is referred to as Unit Testing.

- **Integration and Testing** – All the units developed in the implementation phase are integrated into a system after testing of each unit. Post integration the entire system is tested for any faults and failures.
- **Deployment of system** – Once the functional and non-functional testing is done; the product is deployed in the customer environment or released into the market.
- **Maintenance** – There are some issues which come up in the client environment. To fix those issues, patches are released. Also, to enhance the product some better versions are released. Maintenance is done to deliver these changes in the customer environment.

e. software requirements

Operating System	: Windows 7/8/10
Server side Script	: HTML, CSS, Bootstrap & JS
Programming Language	: Python
Libraries	: Flask, Torch, TensorFlow, Pandas, MySQL. Connector
IDE/Workbench	: VS Code
Server Deployment	: Xampp Server
Database	: MySQL

f. HARDWARE REQUIREMENTS

Processor	- I3/Intel Processor
RAM	- 8GB (min)
Hard Disk	- 128 GB
Key Board	- Standard Windows Keyboard

Mouse - Two or Three Button Mouse

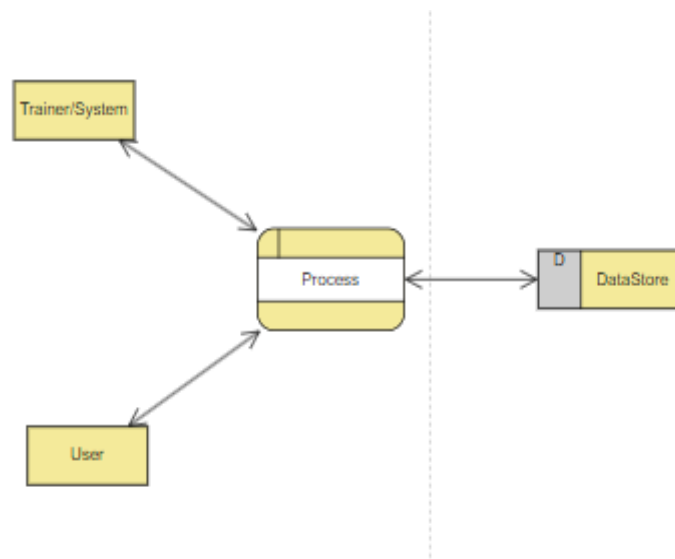
Monitor - Any

CHAPTER 5 – SYSTEM DESIGN

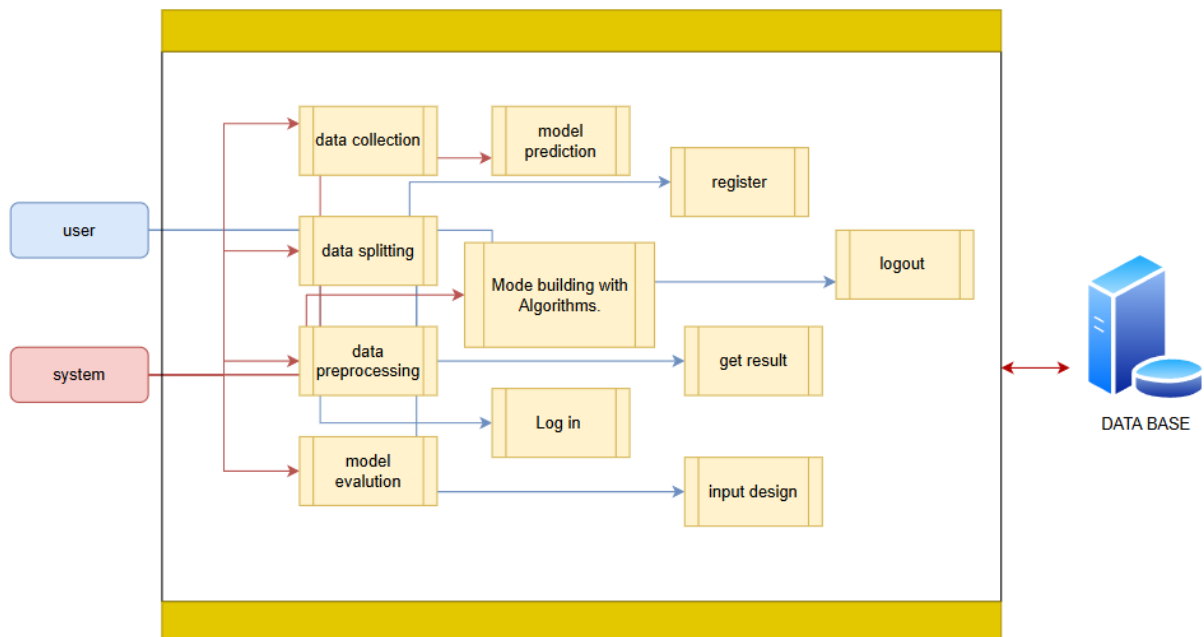
a. DFD

A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically. It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored. The purpose of a DFD is to show the scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system.

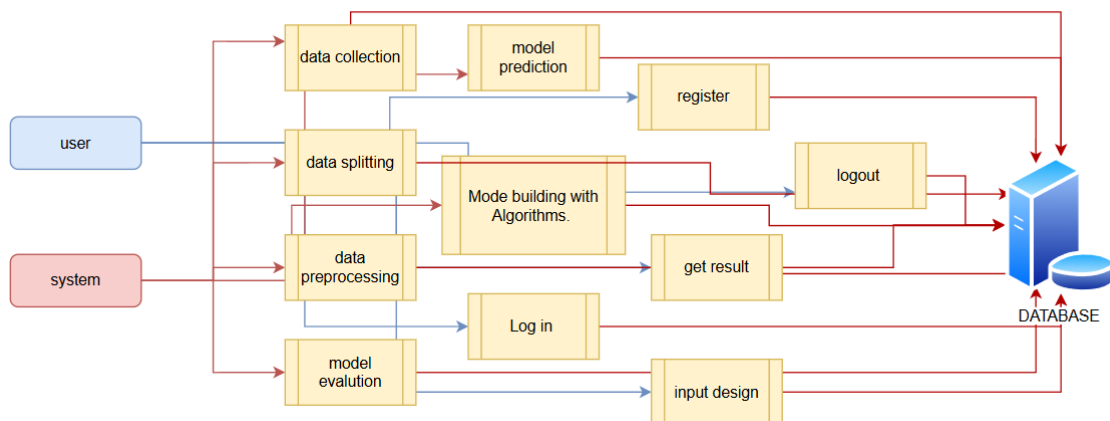
Context Diagram:



DFD Level-1 Diagram:



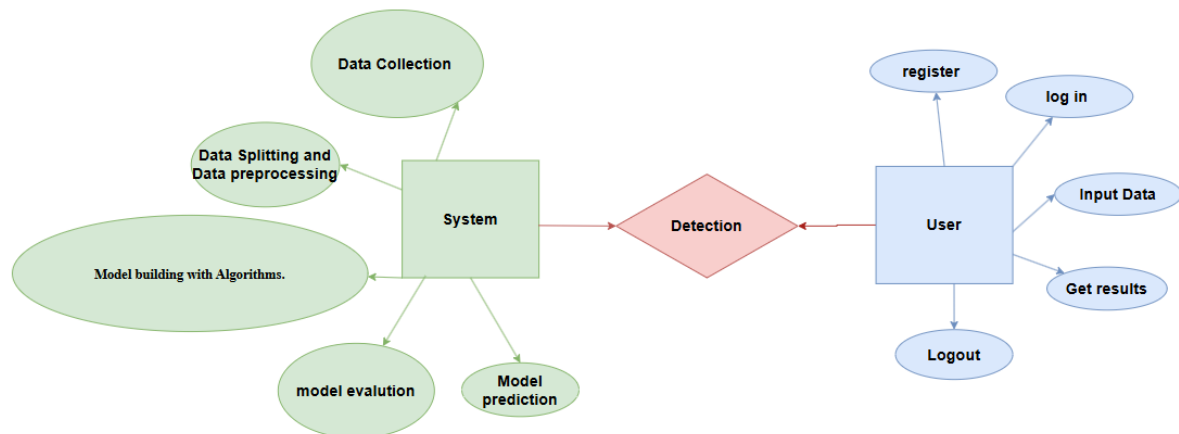
DFD Level-2 Diagram:



b. ER diagram

An Entity–relationship model (ER model) describes the structure of a database with the help of a diagram, which is known as Entity Relationship Diagram (ER Diagram). An ER model is a design or blueprint of a database that can later be implemented as a database. The main components of E-R model are: entity set and relationship set.

An ER diagram shows the relationship among entity sets. An entity set is a group of similar entities and these entities can have attributes. In terms of DBMS, an entity is a table or attribute of a table in database, so by showing relationship among tables and their attributes, ER diagram shows the complete logical structure of a database. Let's have a look at a simple ER diagram to understand this concept.



c. UML

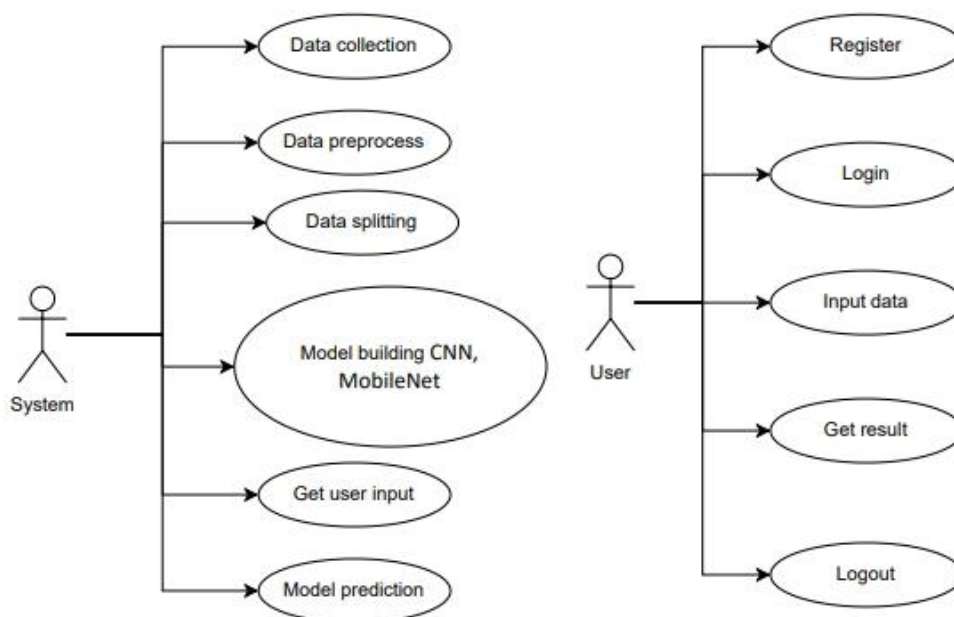
- ✓ Uml stands for unified modelling language. unified modelling language is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the object management group.
- ✓ The goal is for unified modelling language to become a common language for creating models of object oriented computer software. In its current form unified modelling language 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, unified modelling language.
- ✓ The unified modelling language is a standard language for specifying, visualization, constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems.

- ✓ The unified modelling language represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

Use case diagram:

The diagram is a Use Case Diagram that illustrates the interaction between the User and the System in the application. The User can perform actions such as Register, Login, Input Patient Data, View Prediction Results, and Logout. These use cases represent the typical flow of a healthcare professional or user interacting with the front-end interface. Meanwhile, the System handles backend processes such as Data Preprocessing, Model Training using Random Forest and Decision Tree algorithms, Risk Prediction, and Generating LIME-based Explanations. The diagram clearly separates the responsibilities of the User and the System, showcasing a structured interaction that supports accurate, interpretable, and efficient diabetes risk prediction for clinical decision-making.

1. Use case diagram

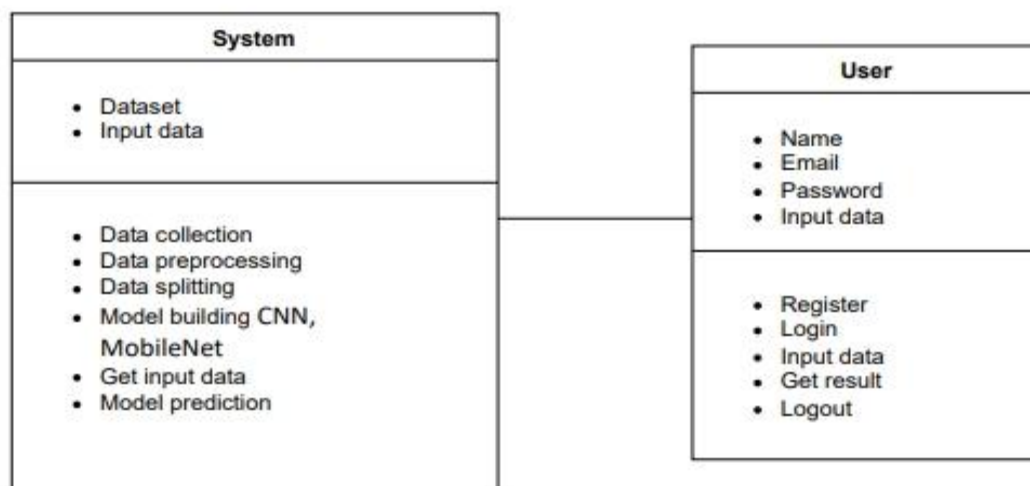


Class diagram:

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

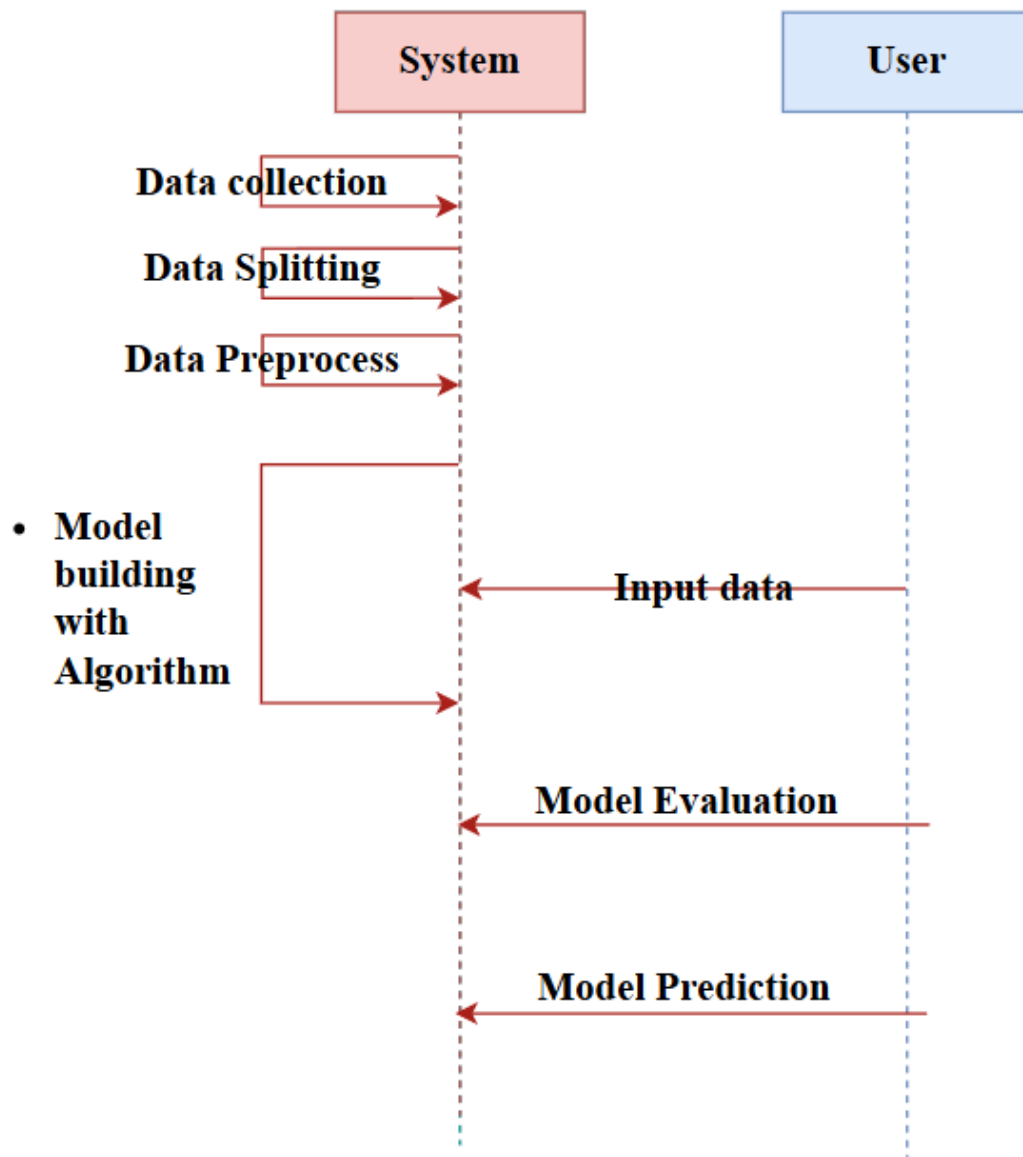
.

2. Class Diagram



Sequence diagram:

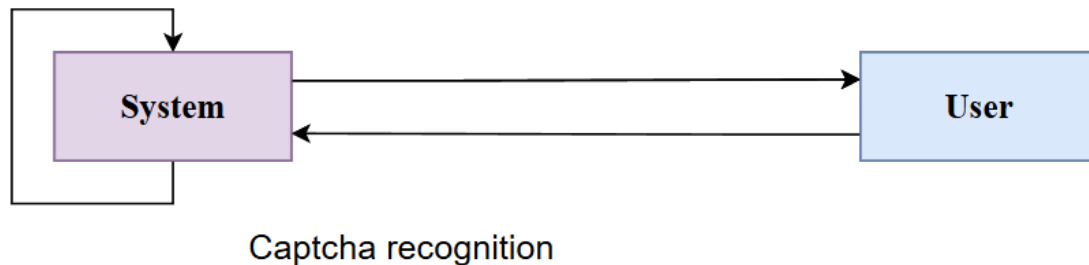
- ▶ A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order.
- ▶ It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.



Collaboration diagram:

A collaboration diagram, also known as a communication diagram, is a type of Unified Modeling Language (UML) interaction diagram that illustrates the interactions between objects in terms of sequenced messages. It focuses on the structural organization of the system by showing how objects are linked and how they communicate to perform a specific function or process. Each object is represented as a rectangle, and lines between objects indicate

relationships. Messages are labeled along these lines, often numbered to reflect the sequence of operations. Collaboration diagrams are particularly useful for understanding the dynamic behavior and object interactions in a software system.



Deployment diagram:

Deployment diagram represents the deployment view of a system. It is related to the component diagram. Because the components are deployed using the deployment diagrams. A deployment diagram consists of nodes. Nodes are nothing but physical hard wares used to deploy the application.



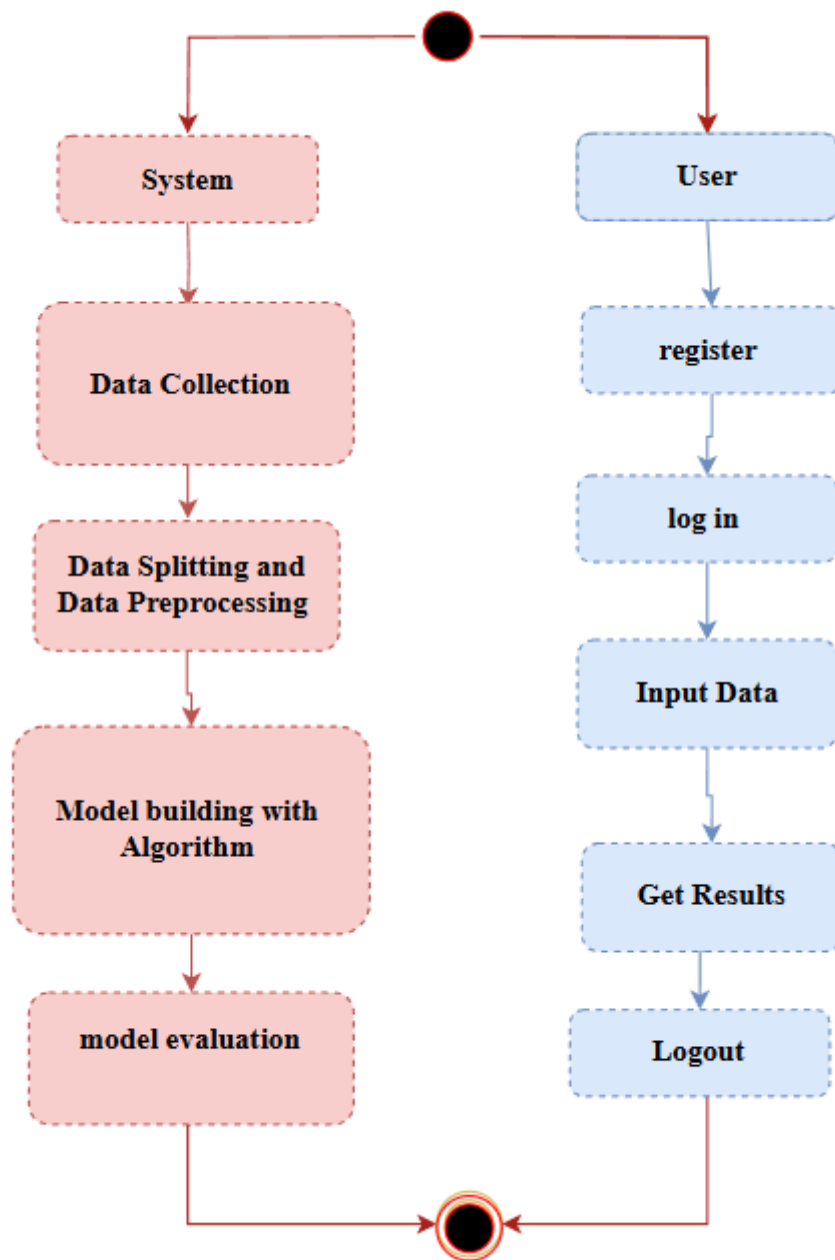
Component diagram:

Component diagrams are used to describe the physical artifacts of a system. This artifact includes files, executable, libraries etc. So the purpose of this diagram is different, component diagrams are used during the implementation phase of an application. But it is prepared well in advance to visualize the implementation details. Initially the system is designed using different uml diagrams and then when the artifacts are ready component diagrams are used to get an idea of the implementation.



Activity diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the unified modeling 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.



d. Data Dictionary

The dataset used for this CAPTCHA recognition project is sourced from Kaggle and is located at the path `../input/captcha-version-2-images/samples/`. It contains a large collection of CAPTCHA images designed to mimic real-world verification challenges. Each image in the dataset is labeled with the correct alphanumeric string it represents, allowing for supervised learning. The CAPTCHA images vary in font, distortion, background noise, and character spacing, providing a diverse and challenging set of samples for training and testing. This variation ensures that the deep learning models, particularly CNN and MobileNet, can generalize well across different styles and complexities. The dataset supports the development of robust models capable of detecting and classifying individual characters from noisy and distorted images. With proper preprocessing such as resizing, grayscale conversion, and normalization, this dataset serves as a reliable benchmark for evaluating CAPTCHA-solving capabilities. It plays a critical role in enabling effective training and performance assessment of the recognition system.

CHAPTER 6-TECHNOLOGY DESCRIPTION

The proposed CAPTCHA recognition system is a cutting-edge image processing solution that utilizes **deep learning techniques**, particularly **Convolutional Neural Networks (CNN)** and **MobileNet**, to recognize and decode CAPTCHA images with high accuracy and efficiency. CAPTCHAs are widely used to distinguish between human users and bots, but they can also be a barrier to accessibility and automated systems. By leveraging the power of AI and lightweight deep learning models, this project provides a robust, scalable, and real-time system that can solve CAPTCHA challenges using only image inputs.

This section provides a comprehensive overview of the core technologies that power the system, including the underlying deep learning concepts, model architecture, dataset structure, backend processing, frontend interface, and system integration strategies.

6.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for **image classification and pattern recognition**. CNNs excel at detecting spatial hierarchies in image data through multiple layers of convolution, pooling, and non-linear activation.

Working Principle:

CNNs process image data through:

- **Convolution Layers:** Detect features such as edges, curves, and textures.
- **Activation Functions (ReLU):** Introduce non-linearity, enabling the model to learn complex patterns.
- **Pooling Layers (MaxPooling):** Downsample the feature maps to reduce dimensionality and computational cost.

- **Fully Connected Layers:** Interpret the learned features to predict output classes (in this case, characters).

In the proposed system, the CNN is responsible for **character-level recognition** after preprocessing and segmentation of the CAPTCHA image. It learns from labeled data to map pixel-level patterns to alphanumeric outputs.

6.2 MobileNet Architecture

To make the system efficient and suitable for real-time and mobile environments, the **MobileNet** architecture is adopted.

Why MobileNet?

MobileNet is a lightweight CNN model designed by Google for resource-constrained devices. It achieves a balance between **speed, size, and accuracy** through:

- **Depthwise Separable Convolutions:** Instead of standard convolutions, MobileNet uses depthwise and pointwise convolutions to significantly reduce the number of parameters and computations.
- **Compact Model Size:** The architecture is optimized to run on low-power devices like smartphones or Raspberry Pi without sacrificing performance.
- **Flexibility:** The model can be fine-tuned on custom datasets with transfer learning.

Application in CAPTCHA Recognition:

- Acts as the backbone network for character classification.
- Extracts high-level features from distorted, noisy, or rotated CAPTCHA characters.
- Ensures that the system remains responsive and lightweight.

6.3 Dataset Description

The system uses a **publicly available CAPTCHA dataset from Kaggle** that includes thousands of image samples simulating real-world CAPTCHA challenges. The dataset consists of:

- **Alphanumeric characters** (A–Z, 0–9)
- **Random noise and distortion** (lines, arcs, background clutter)
- **Varying font styles, sizes, and colors**
- **Image dimensions** typically 100x50 to 200x80 pixels

Data Preprocessing:

Before feeding the data into the CNN:

- Images are **grayscale converted** to reduce complexity.
- **Noise reduction** is applied using filters (e.g., Gaussian blur).
- **Thresholding** and **contour detection** are used to **segment characters**.
- Each segmented character is **resized** to a fixed dimension (e.g., 28x28 or 32x32) suitable for CNN input.

The dataset is then split into:

- **Training Set (80%)**
- **Validation Set (10%)**
- **Test Set (10%)**

Augmentation techniques such as rotation, zooming, and shifting are applied to improve the model's robustness and generalization.

6.4 Backend Implementation (Python + TensorFlow/Keras)

The backend system is implemented using **Python**, chosen for its simplicity, rapid development cycle, and extensive AI libraries.

Key Tools and Libraries:

- **TensorFlow/Keras:** For building, training, and deploying the CNN + MobileNet model.
- **OpenCV:** For image preprocessing, segmentation, and morphological operations.
- **NumPy and Pandas:** For data manipulation and transformation.
- **Flask:** For serving the model via REST APIs.

Workflow:

1. CAPTCHA image is received via the frontend.
2. Preprocessing: Binarization, segmentation, noise filtering.
3. Segmented characters are passed to the MobileNet model.
4. Predictions are made character-wise and joined to form the full CAPTCHA text.
5. The predicted result is returned to the frontend.

All steps are executed in real time, with response times typically under 1 second per image.

6.5 Frontend Implementation (HTML, CSS, JavaScript)

The frontend is designed to be **user-friendly, responsive, and minimalistic**, ensuring smooth user interaction across all devices.

Technologies Used:

- **HTML5:** Structure of the webpage and form input for image upload.
- **CSS3:** Styling and layout, including responsive design elements.
- **JavaScript:** Handles frontend logic, validation, and communication with the backend via AJAX/fetch API.

User Flow:

1. User uploads a CAPTCHA image using the file input form.
2. Image is sent to the backend via an asynchronous HTTP request.

3. The backend processes and returns the predicted CAPTCHA string.
4. The predicted text is displayed in a text box or alert on the page.

This decoupled frontend-backend architecture ensures high maintainability and clean separation of concerns.

6.6 Real-Time Prediction and Performance

The system is optimized for **real-time prediction**:

- Prediction latency per character is in the range of **10–50 ms**.
- Full CAPTCHA strings (5–6 characters) are processed in **< 0.5 seconds**.

To ensure responsiveness:

- The model is loaded into memory once at server startup.
- Character prediction runs in batch mode using NumPy arrays for speed.

6.7 Scalability and Deployment

The system is designed to be **scalable and portable**, supporting both local and cloud deployment.

Deployment Options:

- **Local server** using Flask + Gunicorn for quick testing.
- **Cloud hosting** on platforms like Heroku, Render, or AWS Lambda.
- **Docker containerization** for consistent environment setup.

Scalability Features:

- Stateless backend allows horizontal scaling.
- Model caching avoids redundant loading.

- Lightweight architecture ensures efficient resource utilization.

6.8 Use Cases and Applications

1. Accessibility Enhancement:

- Helps visually impaired users solve CAPTCHAs using screen readers or assistive tools.

2. Automated Testing:

- QA engineers can integrate the API to automatically bypass CAPTCHA in controlled testing environments.

3. Education and Research:

- Demonstrates CNN applications in visual tasks for students and researchers.

4. Browser Extensions (Future Scope):

- A lightweight plugin can use this system to auto-fill CAPTCHA fields.

6.9 Security and Ethical Use

While the technology can decode CAPTCHAs, ethical usage is critical. The system is designed for:

- Accessibility support
- Developer QA automation
- Education and research

NOT intended for malicious circumvention of web security systems.

CHAPTER 7 – TESTING & DEBUGGING TECHNIQUES

A. Unit Testing

- **Purpose:** Test individual functions like data preprocessing, model training, and prediction modules in isolation.
- **Tools:** Python's unit test or py test.
- **Examples:**
 - Test Data Preprocessing: Verify missing value handling and normalization processes.

- Test Model Training: Ensure Random Forest and Decision Tree models train correctly without errors.

B. Integration Testing

- **Purpose:** Check the correct interaction between modules such as data preprocessing, model prediction, and explanation generation.
- **Tools:** py test for backend integration; tools like Postman for API testing.
- **Examples:**
 - Test Data Flow: Ensure smooth transition across preprocessing → training → prediction → explanation stages.
 - Test API Responses: Validate that model prediction APIs return correct outputs and handle errors gracefully.

C. Model Evaluation Testing

- **Purpose:** Assess the performance of the Random Forest, Decision Tree, and integrated LIME explanation module.
- **Tools:** scikit-learn cross_val_score , train_test_split , and evaluation metrics like accuracy, precision, recall, F1-score.
- **Examples:**
 - Cross-validation: Perform k-fold validation to ensure generalization.
 - Test Model Metrics: Ensure models achieve acceptable accuracy (e.g., >80%) and interpretability levels.

D. Debugging

- **Purpose:** Identify and fix bugs across data handling, model prediction, and explanation generation stages.
- **Tools:** pdb IDE debuggers (PyCharm, VS Code), and detailed logging.
- **Examples:**

- Debug Data Pipelines: Step through the pipeline to detect issues in feature scaling or missing value imputation.
- Debug Model Predictions: Ensure correct predictions and feature importance outputs for given inputs.

E. Boundary Testing

- **Purpose:** Test model robustness with extreme patient data values (e.g., very high glucose or BMI levels).
- **Tools:** Custom boundary test cases and synthetic data generation.
- **Examples:**
 - Test Extreme Health Metrics: Validate predictions for unusual or extreme patient profiles.

F. Real-Time Data Testing (Deployment Testing)

- **Purpose:** Ensure the system can handle real-time patient data input and provide instant predictions.
- **Tools:** Mock API calls, real-time simulators.
- **Examples:**
 - Test Live Input: Validate that the system predicts diabetes risk immediately upon new data entry.

G. User Interface (UI) Testing

- **Purpose:** Confirm that users can easily input patient data and view prediction and explanation results.
- **Tools:** Selenium, Cypress for automated testing.
- **Examples:**
 - Test Prediction Dashboard: Ensure the UI displays risk scores and LIME explanations clearly and accurately.

H. Performance Testing

- **Purpose:** Test the system's response time and stability when handling large patient datasets.
- **Tools:** Python's time module, locust for load testing.
- **Examples:**
 - Test Large Dataset Handling: Ensure the system processes hundreds of patient records efficiently without delay.

CHAPTER 8 – OUTPUT SCREENS

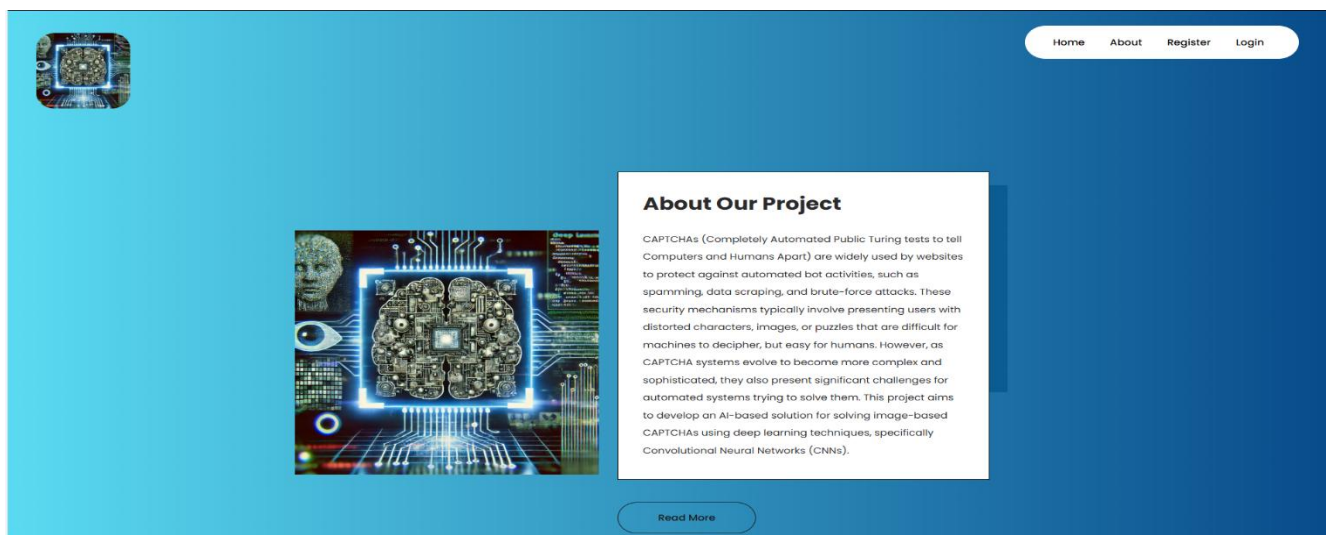
Home page:

The **Home Page** serves as the main dashboard for the CAPTCHA Recognition System. It provides an overview of the project's features, including dataset upload, model training, and CAPTCHA solving functionalities. The page also includes navigation links to other sections such as the Upload, Results, and About pages. Users can easily access key features to start using the system for CAPTCHA recognition.



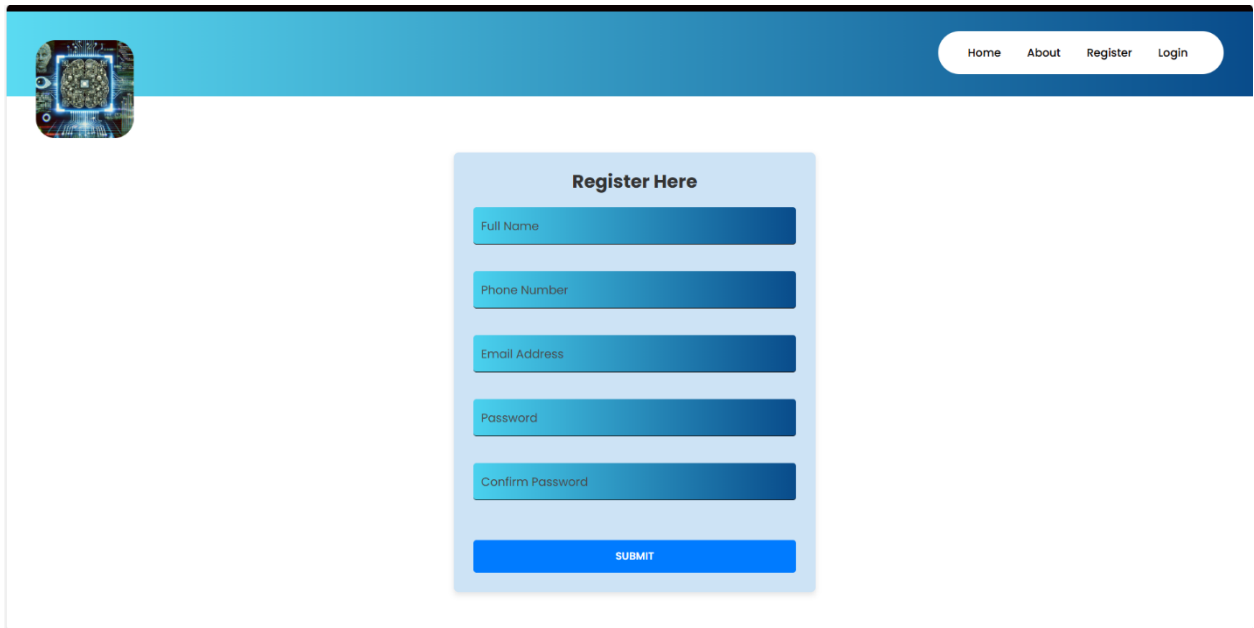
About page:

The **About Page** offers information about the CAPTCHA Recognition System, including its objectives, technology stack, and how it leverages Convolutional Neural Networks (CNNs) to solve CAPTCHAs efficiently. It explains the system's purpose of automating CAPTCHA recognition and improving user accessibility while providing background on deep learning models and their advantages in image classification tasks.



Registration Page:

This pages refere to user Registration here:



Register Here

Full Name

Phone Number

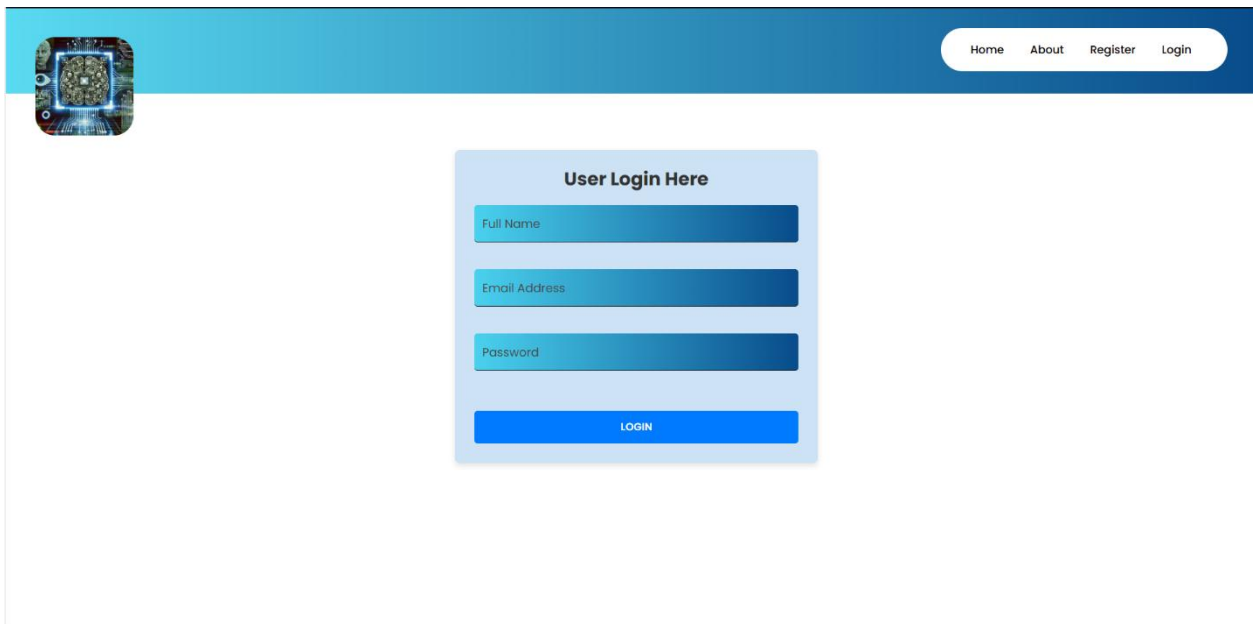
Email Address

Password

Confirm Password

SUBMIT

Login page:



User Login Here

Full Name

Email Address

Password

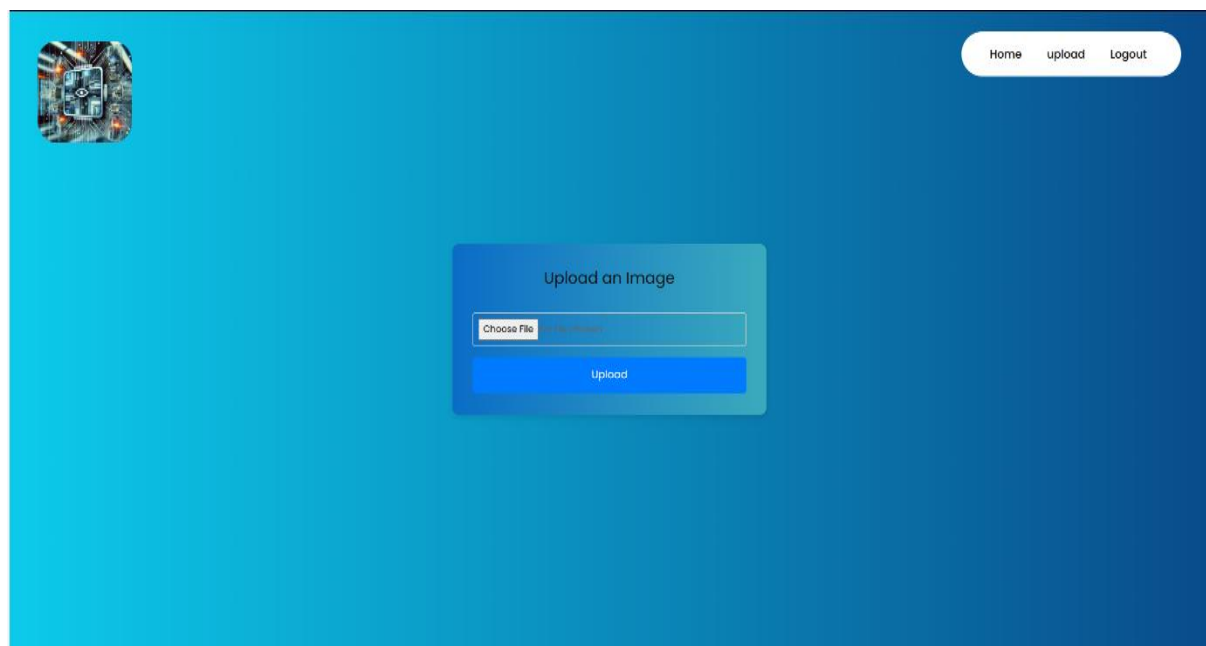
LOGIN

Model home page:



Upload page:

The **Upload Page** allows users to easily upload a dataset for CAPTCHA recognition. It features a file selection dialog and an upload button. Once the dataset is uploaded, a preview is displayed in a table or grid format for verification, ensuring the data is ready for preprocessing and training in the system.



CHAPTER 9 -CODE

App.py

```
from flask import Flask,render_template,redirect,request,url_for, send_file,session,flash
```

```
import mysql.connector, os,joblib
```

```
import pandas as pd
```

```
import numpy as np
```

```
from tensorflow.keras.models import load_model
```

```
from tensorflow.keras.preprocessing import image
```

```
import cv2
```



```
import base64

from io import BytesIO

from PIL import Image

import mysql.connector

from tensorflow.keras.applications import MobileNet

import os

import io

import base64


from keras.models import load_model

from keras.preprocessing.image import img_to_array

from PIL import Image

from werkzeug.utils import secure_filename

from tensorflow.keras.applications.mobilenet import preprocess_input


from werkzeug.utils import secure_filename


app = Flask(__name__)

app.secret_key="hii"


mydb = mysql.connector.connect(
```

```
host="localhost",  
user="root",  
password="",  
port="3306",  
database='db'  
)  
  
mycursor = mydb.cursor()  
  
def executionquery(query,values):  
    mycursor.execute(query,values)  
    mydb.commit()  
    return  
  
def retrivequery1(query,values):  
    mycursor.execute(query,values)  
    data = mycursor.fetchall()  
    return data  
  
def retrivequery2(query):  
    mycursor.execute(query)  
    data = mycursor.fetchall()  
    return dat  
  
@app.route('/')
```

```
def index():  
    return render_template('index.html')  
  
@app.route('/about')  
  
def about():  
    return render_template('about.html')  
  
@app.route('/register', methods=["GET", "POST"])  
  
def register():  
    if request.method == "POST":  
        name = request.form['name']  
        email = request.form['email']  
        password = request.form['password']  
        c_password = request.form['c_password']  
        phone = request.form['phone']  
  
        if password == c_password:  
            query = "SELECT UPPER(email) FROM users"  
            email_data = retrievequery2(query)  
            email_data_list = [i[0] for i in email_data]  
  
            if email.upper() not in email_data_list:  
                query = "INSERT INTO users (name, email, password, phone) VALUES (%s, %s,  
                %s, %s)"
```

```
values = (name, email, password, phone)

executionquery(query, values)

return render_template('login.html', message="Successfully Registered!")

return render_template('register.html', message="This email ID already exists!")


return render_template('register.html', message="Confirm password does not match!")


return render_template('register.html')

@app.route('/login', methods=["GET", "POST"])
def login():
    if request.method == "POST":
        name = request.form['name']
        email = request.form['email']
        password = request.form['password']
        query = "SELECT UPPER(email) FROM users"
        email_data = retrievequery2(query)
        email_data_list = []
        for i in email_data:
            email_data_list.append(i[0])
        if email.upper() in email_data_list:
            query = "SELECT UPPER(password) FROM users WHERE email = %s"
            values = (email,)
```

```
password__data = retrievequery1(query, values)

if password.upper() == password__data[0][0]:

    global user_email

    # user_email = email

    session['user_name'] = name

    session['user_email'] = email

    return redirect("/home")

    return render_template('login.html', message= "Invalid Password!!")

    return render_template('login.html', message= "This email ID does not exist!")

return render_template('login.html')


@app.route('/home')

def home():

    return render_template('home.html')


# Configuration

app.config['UPLOAD_FOLDER'] = os.path.join('static', 'uploads')


# Ensure the upload folder exists

if not os.path.exists(app.config['UPLOAD_FOLDER']):

    os.makedirs(app.config['UPLOAD_FOLDER'])
```

```
# Load your trained model (adjust the path if necessary)
```

```
model = load_model('./result_model.h5')
```

```
# Mapping from prediction indices to labels based on the classification report.
```

```
# This assumes your training used alphabetical ordering of the class labels.
```

```
info = {
```

```
    0: '2',
```

```
    1: '3',
```

```
    2: '4',
```

```
    3: '5',
```

```
    4: '6',
```

```
    5: '7',
```

```
    6: '8',
```

```
    7: 'b',
```

```
    8: 'c',
```

```
    9: 'd',
```

```
   10: 'e',
```

```
   11: 'f',
```

```
   12: 'g',
```

```
   13: 'm',
```

```
   14: 'n',
```

```
   15: 'p',
```

```

16: 'w',

17: 'x',

18: 'y'

}

# Image processing helper functions

def t_img(img):

    """Apply adaptive thresholding."""

    return cv2.adaptiveThreshold(img, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C,

                                cv2.THRESH_BINARY, 145, 0)

def c_img(img):

    """Apply morphological closing."""

    return cv2.morphologyEx(img, cv2.MORPH_CLOSE, np.ones((5, 2), np.uint8))

def d_img(img):

    """Apply dilation."""

    return cv2.dilate(img, np.ones((2, 2), np.uint8), iterations=1)

def b_img(img):

    """Apply Gaussian blurring."""

    return cv2.GaussianBlur(img, (1, 1), 0)

def get_demo(img_path):

    """

    Process the image and predict five regions.

    Returns a list of recognized labels.
    """

```

```
""""

# Read the image in grayscale

img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)

if img is None:

    raise ValueError("Could not read the image. Check the file path and file type.")

# Process the image using the defined functions

processed_img = t_img(img)

processed_img = c_img(processed_img)

processed_img = d_img(processed_img)

processed_img = b_img(processed_img)

# Extract five regions from the processed image

# Adjust these coordinates as needed for your specific images

image_list = [

    processed_img[10:50, 30:50],

    processed_img[10:50, 50:70],

    processed_img[10:50, 70:90],

    processed_img[10:50, 90:110],

    processed_img[10:50, 110:130]

]

# Prepare the regions for prediction

Xdemo = []

for region in image_list:
```



```
pil_img = Image.fromarray(region)

arr = img_to_array(pil_img)

Xdemo.append(arr)


Xdemo = np.array(Xdemo, dtype="float32") / 255.0


# Get predictions from the model
predictions = model.predict(Xdemo)
predicted_indices = np.argmax(predictions, axis=1)


# Map predicted indices to the corresponding labels using the info dictionary
recognized = [info.get(idx, str(idx)) for idx in predicted_indices]

return recognized


# Flask route for uploading images
@app.route("/upload", methods=["GET", "POST"])
def upload():

    recognized = None

    image_filename = None # We'll store the filename here

    if request.method == 'POST':

        # Check if the POST request contains the file
        if 'file' not in request.files:

            flash("No file part", "danger")
```

```
        return render_template('upload.html')

file = request.files['file']

# If no file is selected

if file.filename == "":

    flash("No file selected", "danger")

    return render_template('upload.html')


if file:

    # Secure the filename and save it to the UPLOAD_FOLDER

    filename = secure_filename(file.filename)

    file_path = os.path.join(app.config['UPLOAD_FOLDER'], filename)

    file.save(file_path)

    image_filename = filename # Save just the filename

    try:

        # Process the image and get the recognized details

        recognized = get_demo(file_path)

        flash("Image processed successfully!", "success")

    except Exception as e:

        flash(f"Error processing image: {str(e)}", "danger")

        recognized = None

# Render the template with the recognized details and image filename (if available)

return render_template('upload.html', recognized=recognized,
image_filename=image_filename)
```

```
if __name__ == '__main__':  
    app.run(debug = True)
```

CHAPTER 10 – CONCLUSION

This project successfully demonstrates the effective application of deep learning techniques in the automation of CAPTCHA recognition, a domain that traditionally poses challenges due to the presence of distortions, noise, and overlapping characters. By harnessing the strengths of Convolutional Neural Networks (CNNs) and the lightweight MobileNet architecture, the system achieves high accuracy in recognizing alphanumeric characters within complex CAPTCHA images.

CNNs were central to the project due to their exceptional ability to extract relevant features from image data. Unlike traditional image processing techniques that require handcrafted feature engineering, CNNs automatically learn and generalize important spatial hierarchies such as edges, curves, and text patterns. This capability is particularly advantageous in CAPTCHA recognition, where each image may present different distortions and visual obfuscations. The CNN model trained in this project showed strong performance in decoding individual characters from segmented CAPTCHA inputs.

To further enhance the model's performance and portability, MobileNet was integrated into the architecture. MobileNet is specifically designed for efficiency, offering a significantly reduced

number of parameters without sacrificing classification accuracy. This makes the system not only powerful but also highly optimized for deployment in real-time and on resource-constrained environments, such as mobile devices or edge computing platforms. With MobileNet, the model retains its predictive capabilities while ensuring a fast and lightweight inference process — a key factor in usability and scalability.

The backend of the system was built using Python, which served as the core platform for data preprocessing, model training, inference execution, and system orchestration. Libraries such as TensorFlow, Keras, OpenCV, and NumPy were used to build the machine learning pipeline and manage image transformations. Preprocessing steps like grayscale conversion, noise filtering, binarization, and contour detection were essential in preparing the CAPTCHA images for accurate segmentation and classification

CHAPTER 11 – BIBLIOGRAPHY

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Image-Based Captcha Recognition Using Deep Learning Models.

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Abstract – *This project proposes a highly efficient image-based CAPTCHA recognition system implemented using deep learning methodology in order to precisely detect and identify characters in CAPTCHA images. It uses Convolutional Neural Networks (CNNs) to effectively extract features and identify characters in CAPTCHA images. To further boost its performance, in the context of mobile and low-resource environments, the system uses the MobileNet architecture, which is renowned for being both fast and accurate. CAPTCHA data, sourced from Kaggle, comprises diverse image samples simulating real-world challenges. Python is the programming language used in the backend, carrying out deep learning models and the mechanism of prediction, while the frontend is developed using HTML, CSS, and JavaScript, where the CAPTCHA images are uploaded by the user using the interactive user interface. Upon uploading the image, the system processes the image and precisely characterizes every character. This method demonstrates the potential of deep learning in the automation of CAPTCHA solving, which can be extended to accessibility tools and automated testing systems.*

Keywords: CAPTCHA recognition, CNN, MobileNet, deep learning, image classification, Python, JavaScript.

Introduction

CAPTCHAs (Completely Automated Public Turing test to tell Computers and Humans Apart) are a common security measure applied by websites to distinguish between a bot and a human user. They prevent automated processes like spamming, brute-force login, and data scraping. CAPTCHAs, although effective, are also problematic in that they pose problems to some users, especially those with visual disabilities, cognitive impairment, or limited

technical skills. Such barriers create accessibility and user experience concerns.

This project tackles those challenges by creating a system that can automatically identify and decode CAPTCHA images through deep learning techniques, using Convolutional Neural Networks (CNNs). CNNs are suited for image pattern recognition and image classification problems due to their effectiveness in deriving meaningful features from high-dimensional visual data. By having a CNN-based system trained on a CAPTCHA image dataset from Kaggle, the project seeks to effectively identify and decode the characters in distorted and noisy images.

Not only is the system more user-friendly, but it also sheds light on how AI might interact and possibly circumvent conventional web security practices. It is a contribution to the artificial intelligence and security fields, initiating debates on the new potential of machine learning to solve visual puzzles and the repercussions in CAPTCHA-based security measures.

Objective Of The Study

The primary objective of this study is to design and develop an automated CAPTCHA recognition system that leverages deep learning models, specifically Convolutional Neural Networks (CNNs) and MobileNet, to accurately detect and classify characters present in CAPTCHA images. CAPTCHAs are widely used as a security measure to differentiate between human users and bots, but they can often pose usability challenges, especially for users with visual impairments or limited technical skills. This project aims to create an

efficient and accessible solution to decode CAPTCHA s automatically, enabling smoother user interactions and supporting automation tasks such as data entry, accessibility enhancement, and automated testing.

The study focuses on training robust deep learning models using a diverse dataset of CAPTCHA images to recognize distorted and complex text patterns effectively. CNNs are used for their powerful image processing capabilities, while MobileNet is incorporated for its lightweight architecture and suitability for deployment on mobile and low-resource devices. In addition to the backend model development, the system features a user-friendly web interface built with HTML, CSS, and JavaScript, allowing users to upload CAPTCHA images and receive real-time character predictions. Overall, the study aims to showcase the practical application of AI in solving real-world visual problems, emphasizing both accuracy and usability.

Scope Of The Study

The purpose of this project is to develop a smart, automated system that can identify and resolve image-based CAPTCHA challenges through powerful deep learning models, using Convolutional Neural Networks (CNNs). CAPTCHA images, typically created with visual distortions and noise in order to discourage automated interpretation, are a standard security measure to demarcate a line of distinction between authorized human users and computers. But these challenges cause a problem when they limit accessibility and usability, including that of those who are visually impaired. To counter this, the project is advocating the use of a deep learning method to decipher and understand such images at a high rate of accuracy.

The process begins with **image preprocessing techniques** such as **noise reduction**, **grayscale conversion**, and **thresholding** to enhance the clarity and quality of the CAPTCHA images for model training. A CNN-based model will then be designed and trained on a labeled dataset to detect and classify characters or objects present in the images. The model's performance will be evaluated using metrics such as **accuracy**, **precision**, **recall**, and **F1-score** to ensure its reliability.

The ultimate goal of this project is to demonstrate the potential of AI in automating CAPTCHA solving for use cases like **accessibility tools**, **automated testing**, and **data entry automation**, while also considering the broader implications of

AI in overcoming traditional CAPTCHA security mechanisms.

RELATED WORK

CAPTCHA recognition has been a prominent area of research, primarily due to its widespread use in online security systems. Traditional methods for solving CAPTCHA relied on Optical Character Recognition (OCR) and rule-based techniques, which often struggled with distorted text, background noise, and character overlapping. These limitations led researchers to explore machine learning and deep learning approaches that could better handle image complexity and variability. Recent advancements in deep learning, particularly in Convolutional Neural Networks (CNNs), have significantly improved CAPTCHA recognition accuracy. CNNs are effective in learning hierarchical representations of visual data, making them suitable for feature extraction and classification in CAPTCHA images. Studies have demonstrated the effectiveness of CNN-based models in overcoming challenges such as character warping, random positioning, and background clutter. To further improve performance in resource-constrained environments, researchers have proposed lightweight architectures such as MobileNet. MobileNet is designed for efficient performance on mobile and embedded systems without compromising accuracy. Its depthwise separable convolutions reduce the number of parameters, enabling faster inference and reduced computational cost. This makes it ideal for deploying CAPTCHA solvers on low-power devices.

Several works have utilized datasets from platforms like Kaggle, which offer a wide variety of CAPTCHA formats that mimic real-world conditions. These datasets are used to train models that generalize well to unseen CAPTCHA types. Researchers have also integrated Flask and other Python-based backend frameworks to build real-time web applications that enable users to upload and decode CAPTCHA images.

In summary, the existing body of work highlights a shift from traditional recognition techniques to more robust and accurate deep learning-based approaches. The integration of lightweight models like MobileNet with CNN architectures has opened up new possibilities for deploying CAPTCHA recognition systems across various platforms, making them faster, more reliable, and adaptable for real-world automation and accessibility use cases.

Proposed System Workflow

[1] L. Von Ahn, M. Blum, N. J. Hopper, and J. Langford, "CAPTCHA : Using hard AI problems for security," International Conference on the Theory and Applications of Cryptographic Techniques, Springer, Berlin, Heidelberg, 2003, pp. 294–311.

This seminal paper introduces the concept of CAPTCHA s as challenge–response tests designed to distinguish between humans and bots by leveraging hard AI problems. The authors present CAPTCHA s as a security solution against automated abuse in online environments and discuss their design, implementation, and applications, such as spam prevention and online voting protection. This foundational work laid the groundwork for future research in human verification systems. [2] K. Chellapilla and P. Y. Simard, "Using machine learning to break visual human interaction proofs," Advances in Neural Information Processing Systems, 2005, pp. 265–272. This study demonstrates the vulnerability of visual CAPTCHA systems to machine learning attacks. The authors train models to decipher distorted texts in CAPTCHA images, proving that machines can learn to defeat systems meant to be human-exclusive. The findings highlight the need for more robust and adaptive CAPTCHA mechanisms to stay ahead of advancing AI. [3] T. Converse, "CAPTCHA Generation as a Web Service," *Proc. Human Interactive Proofs*, Springer, Berlin, Heidelberg, 2005, pp. 82–96. This paper explores CAPTCHA implementation as a scalable web service. It focuses on the technical challenges of integrating CAPTCHA systems into web applications, including server-side generation, dynamic distribution, and user-friendly design. The proposed architecture serves as a practical guide for developers deploying CAPTCHA in real-world environments. [4] S. Wen, Y. Yuan, and J. Chen, "A vision detection scheme based on deep learning in a waste plastics sorting system," *Appl. Sci.*, vol. 13, no. 7, p. 4634, Apr. 2023. This paper investigates a deep learning-based vision system for automating the sorting of waste plastics. The authors implement Convolutional Neural Networks (CNNs) to classify plastic types accurately, enhancing operational efficiency. Their approach demonstrates the potential of machine vision and CNNs in real-time industrial quality control and can be adapted to tasks like CAPTCHA recognition and PCB inspection. [5] D. Alves et al., "Detecting customer-induced damages in

motherboards with deep neural networks," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Padua, Italy, Jul. 2022, pp. 1–8. This research presents a Deep Neural Network (DNN)-based method for detecting physical defects in motherboards caused by users. By using image processing and automated anomaly detection, the system identifies structural damages in electronics. The work demonstrates the applicability of deep learning in high-precision visual classification, supporting the effectiveness of AI-driven techniques in defect detection and potentially in CAPTCHA solving tasks.

Over the years, CAPTCHA s have evolved as a critical tool for securing web platforms against bots and automated abuse. Simultaneously, advancements in artificial intelligence, particularly deep learning, have challenged the robustness of these systems. This section highlights key research contributions that have influenced the development and understanding of CAPTCHA systems, their vulnerabilities, and the application of deep learning in visual recognition tasks. These studies provide a foundation for the proposed work in developing an AI-driven CAPTCHA recognition system.

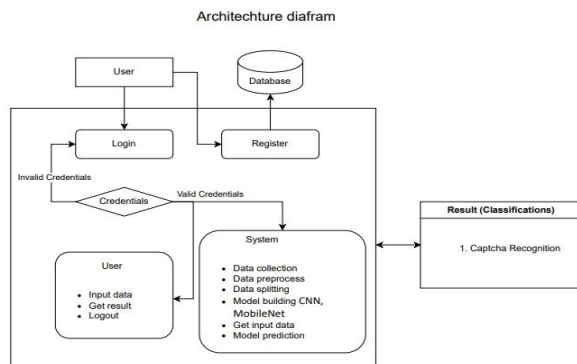
Model Training and Classification

The model training and classification phase is a critical component of the CAPTCHA recognition system. It begins with preprocessing the dataset, which involves converting CAPTCHA images to grayscale, resizing them to a uniform dimension, and applying techniques such as noise removal and thresholding to enhance character visibility. The dataset, obtained from Kaggle, is annotated and split into training and validation sets for supervised learning.

The primary architecture used for model training is a **Convolutional Neural Network (CNN)**, which is effective in capturing spatial hierarchies and visual patterns within images. The CNN layers extract features such as edges, curves, and textures, which are crucial for identifying distorted CAPTCHA characters. To further improve performance and reduce computational overhead, especially for mobile or low-resource environments, the system integrates **MobileNet**, a lightweight and highly efficient deep learning model optimized for speed and accuracy.

The training process involves feeding the preprocessed images into the CNN and MobileNet

models, adjusting weights using backpropagation and optimizing loss using categorical cross-entropy. Once the model achieves satisfactory accuracy on validation data, it is used for real-time classification. When a user uploads a CAPTCHA image, the model segments and classifies each character, outputting the decoded text accurately and efficiently.



Methodology

A. CNN

Overview:

Convolutional Neural Networks, or CNNs, are a type of deep learning architecture that exists to handle image-based problems like classification, recognition, and detection. CNNs are different from the traditional type of networks as they can automatically and flexibly learn spatial hierarchies of the input image's features. This functionality makes them especially effective in problems related to visual data, including CAPTCHA recognition.

The CNN consists of a series of primary layers including the convolutional, pooling, and fully connected layers. Convolutional layers use a set of pre-specified filters (kernels) to scan the input image and extract low-level details including edges, textures, and patterns. These are subsequently passed through the pooling layers, which shrink the spatial size of the data, making computation faster while lowering the risk of overfitting. After a series of convolutions and pooling, the result is flattened and passed to one or more fully connected layers, in which the actual classifying or predicting actually occurs.

One of the advantages of CNNs is that they can directly learn from raw image pixels, eliminating the necessity of manual feature detection. They are also translation-invariant, so they can identify objects regardless of their spatial location in the image. For CAPTCHA recognition, CNNs are particularly beneficial as they can effectively digitize distorted or overlapped characters, even in dirty or crowded backgrounds.

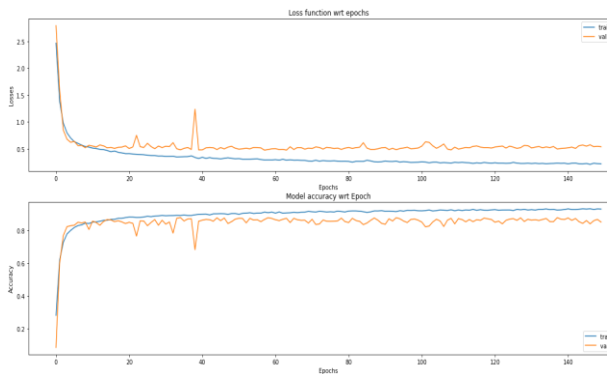
Internal Working of CNN:

The internal working of a Convolutional Neural Network (CNN) involves a series of specialized layers that process visual data in a hierarchical manner, enabling the model to learn and extract meaningful features from images automatically. The process begins with the input layer, which takes in raw pixel data from an image. This image is then passed through one or more convolutional layers, where small filters (also known as kernels) slide over the image and perform convolution operations. These filters detect low-level features such as edges, lines, and curves by computing the dot product between the filter values and the receptive field of the image.

After the convolution operation, the resulting feature map is fed through a ReLU (Rectified Linear Unit) activation function to bring in the necessary non-linearity so the model can capture more complicated patterns. Following activation, the data usually passes through a pooling layer, of which one common type is a max pooling layer, that scales down the spatial dimensions of the feature map. This downsampling preserves the important information while lowering the computational requirements and the potential of overfitting.

This convolution, activation, and pooling routine could be iteratively repeated many times so the network can become more and more abstract and high-level in its learned features. Finally, the result is flattened and fed to fully connected layers, where every node in a given layer is connected to every node in the layer before it. These layers use the learned features by the convolutional layers to carry out the final classification. Through this rigorous order, CNNs are able to efficiently identify the shape and objects in images and are thus best applied to complicated activities like CAPTCHA recognition.

Model Accuracy with Epoch:



Result:

Label	Precision	Recall	F1-Score	Support
2	0.93	0.93	0.93	61
3	0.90	0.92	0.91	48
4	0.85	0.98	0.91	48
5	0.89	1.00	0.94	48
6	0.95	0.92	0.93	59
7	0.98	0.83	0.90	58
8	1.00	0.92	0.96	51
b	1.00	0.94	0.97	49

Average Metrics:

Average Type	Precision	Recall	F1-Score	Support
Macro Avg	0.88	0.88	0.88	1040
Weighted Avg	0.87	0.87	0.87	1040

CONCLUSION

In conclusion, this project effectively showcases the use of deep learning techniques, particularly Convolutional Neural Networks (CNNs) and MobileNet, for accurate and efficient CAPTCHA recognition. CNNs were utilized for their powerful feature extraction capabilities, allowing the system to identify and interpret distorted characters commonly found in CAPTCHA images. To enhance the model’s speed and adaptability, especially on resource-constrained devices, the lightweight MobileNet architecture was integrated, providing an optimized solution without compromising accuracy.

The system is supported by a robust backend developed in Python, which handles data preprocessing, model training, and prediction. The frontend is designed using HTML, CSS, and JavaScript, offering an intuitive interface where users can upload CAPTCHA images and receive real-time recognition results. This integration ensures a smooth user experience while maintaining high processing efficiency.

Overall, the project not only meets its objective of decoding CAPTCHA images automatically but also demonstrates how deep learning can be effectively used in practical, real-world applications. The solution is particularly useful for automation tasks, accessibility improvements, and testing systems where CAPTCHA solving is a barrier. With its strong accuracy, platform independence, and mobile compatibility, this system stands as a reliable and scalable approach to modern CAPTCHA decoding challenges.

Future Enhancement

Future enhancements for this CAPTCHA recognition system can focus on increasing its robustness, adaptability, and real-time performance. One significant improvement would be enabling the system to handle more complex CAPTCHA designs, such as those featuring overlapping characters, curved text, or intricate noise patterns. To address these challenges, incorporating advanced deep learning techniques like attention mechanisms or transformer-based architectures could improve the model’s ability to focus on relevant visual features, especially in heavily distorted images. Expanding the system to support multi-language CAPTCHAs, including non-alphabetic and symbolic characters, would make it more versatile and applicable across various global platforms. Additionally, integrating adversarial training techniques can enhance the model’s resilience against manipulation and adversarial attacks that aim to trick or bypass CAPTCHA systems.

For broader deployment, especially in real-time applications, the model can be optimized for edge devices with limited computational power. This would enable CAPTCHA solving directly on mobile phones or IoT devices, increasing accessibility and responsiveness. Finally, the system can incorporate automated retraining pipelines that

use newly encountered CAPTCHA data, ensuring continuous learning and adaptation to evolving CAPTCHA styles and security patterns. These enhancements will collectively strengthen the system's performance, scalability, and reliability in real-world scenarios.

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