GENEALOGY PREDICTION USING CONVOLUTIONAL NEURAL NETWORKS

A Mini Project Report Submitted
In partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology in Information Technology

by

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CERTIFICATE

This is to certify that this is the bonafide record of the Mini Project entitled **"Genealogy prediction using convolutional neural networks"**, submitted by V.THRIVENI **(21N31A12J7), S.THARUNI(21N31A1242)** of B.Tech in the partial fulfillment of the requirements for the degree of Bachelor of Technology in Information Technology during the year 2024-2025. The results embodied in this mini project report have not been submitted to any other university or institute for the award of any degree or diploma.

Internal Guide	**Head of the Department**
Dr.K.Suresh **Associate Professor**	**Dr.G. Sharada** **Professor**

External Examiner

DECLARATION

We hereby declare that the mini project titled **“Genealogy prediction using convolutional neural networks”** submitted to Malla Reddy College of Engineering and Technology (UGC Autonomous), affiliated to Jawaharlal Nehru Technological University Hyderabad(JNTUH)for the award of the degree of Bachelor of Technology in Information Technology is a result of original work carried-out in this project.It is further declared that the mini project report or any part thereof has not been previously submitted to any University or Institute for the award of degree or diploma.

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With regards and gratitude

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ABSTRACT

Genealogy prediction aims to reconstruct ancestral relationships and trace lineage patterns from genetic data, playing a crucial role in evolutionary biology, medical research, and personalized genomics. Traditional methods rely heavily on statistical models, but recent advances in machine learning have introduced the use of convolutional neural networks (CNNs) to improve accuracy and efficiency.

This abstract outlines the implementation of CNNs for predicting genealogical relationships based on genetic sequences or ancestral datasets. CNNs excel at feature extraction through their ability to automatically identify patterns in large datasets. In genealogy prediction, they can learn and model the hierarchical structure of genetic data, identifying shared genetic markers and mutations across different generations. By applying CNNs, it is possible to enhance the prediction accuracy of ancestral relationships, reducing computational time and handling more complex datasets than traditional methods.

The proposed method involves training a CNN model with labeled genealogical data and using the trained network to predict unknown relationships in test datasets. The performance is evaluated through accuracy metrics, such as precision, recall, and F1 score, compared to other state-of-the-art approaches. Results demonstrate that CNN-based models offer significant improvements in predicting genealogical patterns, particularly when dealing with noisy or incomplete genetic data.

the application of CNNs in genealogy prediction provides a powerful tool for decoding ancestral relationships, with promising potential for advancements in genetics, evolutionary studies, and personalized medicine.

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CHAPTER 1
INTRODUCTION

Genealogy prediction involves understanding and reconstructing ancestral relationships from genetic data, providing insights into evolutionary history, human migration patterns, and disease inheritance. Traditional genealogy prediction methods often rely on statistical approaches such as phylogenetic trees and population genetics models. While these methods have been effective, they face limitations when working with complex or incomplete datasets and may struggle to accurately capture the intricacies of genealogical relationships.

Recent advancements in machine learning, particularly deep learning techniques like convolutional neural networks (CNNs), offer new possibilities for improving genealogy prediction. CNNs are designed to automatically detect patterns and hierarchical features in data, making them well-suited for analyzing genetic sequences and genealogical information. Originally developed for image recognition tasks, CNNs have proven effective in various domains requiring pattern recognition and feature extraction, such as genomics, where large amounts of data can be analyzed efficiently.

In this work, we explore the application of CNNs to genealogy prediction, hypothesizing that the network’s ability to model complex data structures can provide significant improvements over traditional approaches. By leveraging CNNs' capacity to learn directly from genetic data, we aim to enhance the accuracy and robustness of genealogical inferences, especially in scenarios involving incomplete, noisy, or large-scale datasets.

1.1 PROBLEM DEFINITION

Genealogical research aims to uncover family connections, heritage, and inherited traits. However, traditional methods in genealogy, such as reliance on historical records, family trees, and genetic analysis, face significant limitations:

1. **Incomplete or Unavailable Records**: Many families have limited documentation of their ancestry, with historical records often missing, destroyed, or never recorded. This lack of documentation hinders the ability to trace family history accurately, leaving gaps in understanding lineage.
2. **Costly and Limited Genetic Testing**: Genetic testing has become a common tool for verifying biological connections and tracing ancestry. However, it is not universally accessible due to cost and availability. Furthermore, while genetic testing reveals biological links, it doesn't provide information on specific, visually inherited traits, like facial features and expressions, which are often a part of family identity.
3. **Lack of Visual and Physical Trait Analysis**: Existing systems do not effectively utilize photographs or images to determine familial characteristics. Many people seek to understand how certain physical features, such as facial structure, eye shape, or smile, are passed down across generations. Current methods lack the capability to visually connect individuals with their ancestors based on appearance alone, even though these characteristics hold valuable insights into family heritage.

1.2 EXISTING SYSTEM

The existing genealogy systems primarily rely on two key methods:

1. **Historical Records and Documentation**: Traditional genealogy relies heavily on historical records, family trees, and documentation to trace family lineage. However, the completeness and accuracy of these records can vary, and for many, they are often inaccessible or incomplete.
2. **Genetic Testing**: Genetic analysis allows individuals to trace biological lineage and ancestral origins through DNA testing. While highly accurate, genetic testing is costly and limited to providing information on genetic links without revealing non-biological, inheritable traits observable through physical appearance.

Both methods, while beneficial, do not provide comprehensive insight into how familial traits manifest physically across generations.

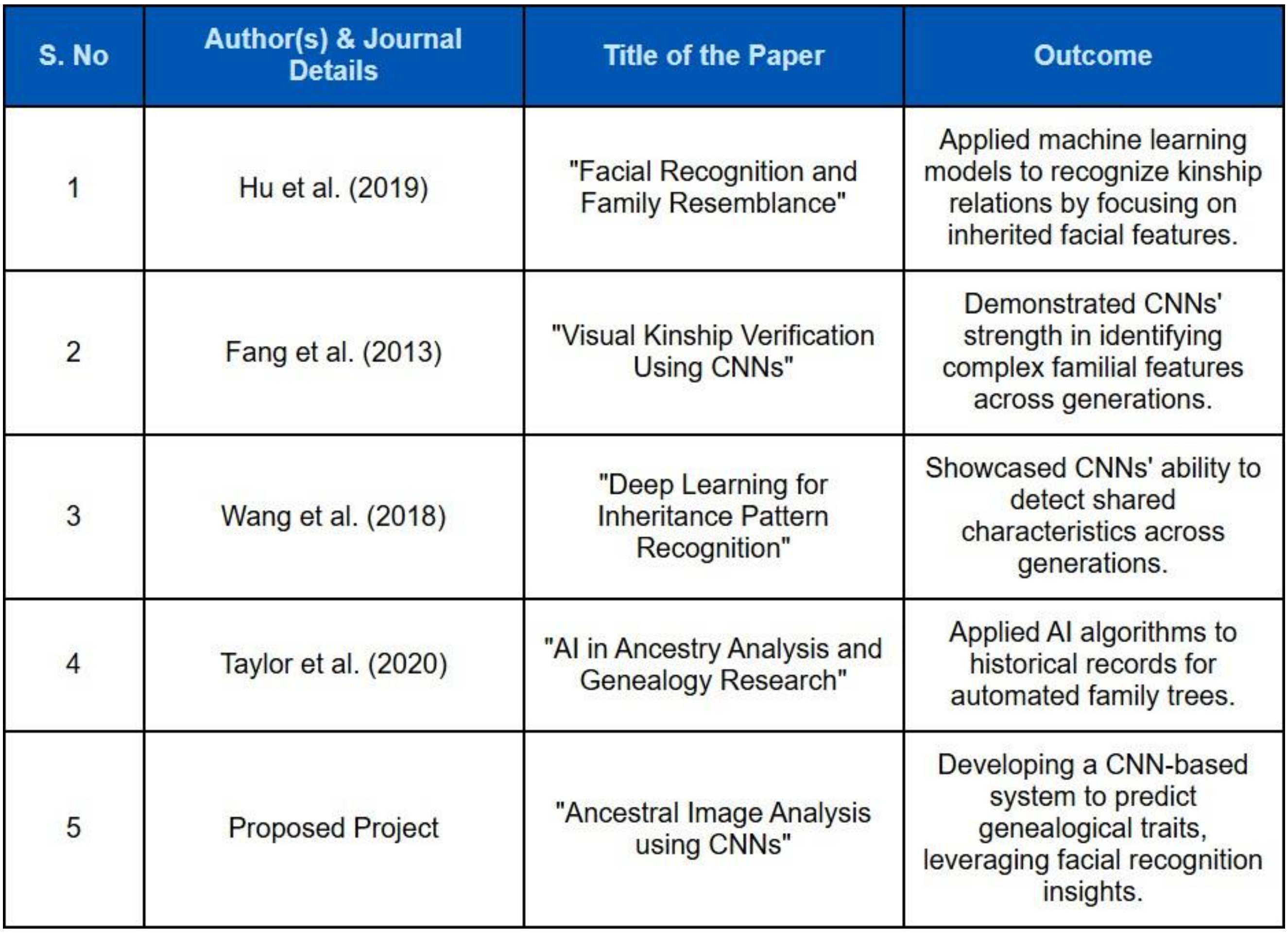
1.3 PROPOSED SYSTEM

Our proposed system addresses these limitations by utilizing convolutional neural networks (CNNs) to predict familial characteristics directly from photographs. By training CNNs on a comprehensive dataset of labelled images spanning multiple generations, we enable the model to recognize intricate patterns in facial features that reflect inheritance. The CNN model processes input images by extracting facial features and comparing them to learned generational patterns within the dataset. This approach allows us to predict an individual’s genealogical traits with a visual representation, introducing a novel method for understanding familial inheritance.

The benefits of this system include:

- **Visual-Based Ancestry Analysis**: Unlike genetic tests, our system provides insights based on physical appearance and inheritable traits visible through images.
- **Accessibility**: This method can serve individuals without access to genetic testing or extensive family records.
- **Data-Driven Ancestry Insights**: By utilizing a data-driven approach, the system can offer a fresh perspective on familial inheritance that complements traditional methods.

1.4 LITERATURE REVIEW



S. No	Author(s) & Journal Details	Title of the Paper	Outcome
1	Hu et al. (2019)	"Facial Recognition and Family Resemblance"	Applied machine learning models to recognize kinship relations by focusing on inherited facial features.
2	Fang et al. (2013)	"Visual Kinship Verification Using CNNs"	Demonstrated CNNs' strength in identifying complex familial features across generations.
3	Wang et al. (2018)	"Deep Learning for Inheritance Pattern Recognition"	Showcased CNNs' ability to detect shared characteristics across generations.
4	Taylor et al. (2020)	"AI in Ancestry Analysis and Genealogy Research"	Applied AI algorithms to historical records for automated family trees.
5	Proposed Project	"Ancestral Image Analysis using CNNs"	Developing a CNN-based system to predict genealogical traits, leveraging facial recognition insights.

CHAPTER 2
SYSTEM REQUIREMENTS

2.1 HARDWARE AND SOFTWARE REQUIREMENTS

HARDWARE REQUIREMENTS:

- **Processor:** AMD Ryzen
- **Hard Disk:** 1 TB SSD
- **RAM:** 16 GB

SOFTWARE REQUIREMENTS:

- **Operating System:** Windows 11
- **Coding Language:** Python 3.x
- **Deep Learning Frameworks:** TensorFlow,Keras
- **Image Processing Libraries:** OpenCV

2.2 SOFTWARE REQUIREMENTS SPECIFICATION

FUNCTIONAL REQUIREMENTS

1. **Upload**: Users can upload photographs for analysis.
2. **Facial Feature Extraction**: The system identifies facial features using CNNs.
3. **Ancestral Trait Prediction**: Predict physical traits of parents and grandparents.
4. **Pattern Recognition**: Compare facial features with learned generational patterns.
5. **Display Results**: Show predicted ancestral traits in a user-friendly format.

NON FUNCTIONAL REQUIREMENTS

1. **Performance**: Predictions should be returned in under 5 seconds.
2. **Scalability**: Support multiple users and large datasets.
3. **Security**: Ensure secure storage and handling of user data.
4. **Usability**: Simple, intuitive interface for easy use.
5. **Accuracy**: Aim for high prediction accuracy (90%+).
6. **Compatibility**: Support common image formats (JPEG, PNG).
7. **Maintainability**: Modular design for easy updates.
8. **Reliability**: Ensure consistent results and high system uptime.

Requirements Analysis:

This requirement analysis establishes a comprehensive framework for developing the genealogy prediction system using convolutional neural networks. By addressing both functional and non-functional requirements, the project aims to deliver a robust, efficient, and user-friendly solution that meets the evolving needs of researchers and practitioners in the fields of genetics and genealogy

Feasibility Analysis:

The feasibility analysis for the proposed genealogy prediction system using convolutional neural networks (CNNs) evaluates its practicality across several dimensions. Technically, the project is viable due to the availability of advanced computational resources, such as high-performance GPUs, and widely-used deep learning frameworks like TensorFlow and PyTorch. Success hinges on having a skilled team with expertise in machine learning, genetics, and bioinformatics, as well as access to comprehensive genetic datasets for training and validation. Economically, while the project entails costs related to software licenses, hardware procurement, and personnel, the potential return on investment is significant, particularly in enhancing genealogical research and opening new avenues in personalized medicine and ancestry services. Operationally, ensuring compatibility with existing genetic data management systems and providing user training will be essential for adoption and acceptance. Legally, the project must comply with regulations regarding genetic data privacy, such as HIPAA and GDPR, necessitating secure data handling and anonymization measures. Overall, the feasibility analysis indicates a positive outlook for the project, balancing technical, economic operations. .

CHAPTER 3

SYSTEM DESIGN

DESCRIPTION

The proposed genealogy prediction system is a cutting-edge solution that leverages convolutional neural networks (CNNs) to streamline and enhance the process of inferring ancestral relationships from genetic data. Designed to handle a variety of genetic information types, such as DNA sequences and single nucleotide polymorphisms (SNPs), this system provides users with the ability to predict genealogical connections with unprecedented accuracy and efficiency. The architecture is built around a comprehensive data input module that facilitates the uploading of genetic data in multiple formats, incorporating sophisticated preprocessing capabilities to ensure that the data is normalized and transformed for optimal analysis.

Central to the system is an advanced CNN model specifically engineered for genealogy prediction. This model features a series of convolutional and pooling layers that automatically learn to extract significant features from the input genetic data, allowing it to discern complex patterns and relationships that traditional methodologies might miss. Coupled with this is a robust training and validation pipeline that empowers users to train the CNN on well-structured, labeled datasets while integrating hyperparameter tuning and performance assessment mechanisms to ensure the model is fine-tuned for accuracy and generalization to new, unseen data.

The user-friendly prediction interface allows for the seamless input of new genetic data, producing genealogical predictions alongside confidence scores to help users gauge the reliability of the results. To further enhance understanding and usability, the system includes visualization tools that effectively communicate the predicted relationships through intuitive graphical representations, such as lineage trees or network diagrams. Security is paramount, and the system incorporates a user management feature that ensures sensitive genetic information is protected through robust authentication and access controls.

3.1 MODULES OF SYSTEM

1. **app.py**
   - **Purpose**: The main application entry point.
   - **Functions**: Initializes the web application, defines routes for image uploads, processes requests, and renders templates. Connects the frontend, backend, and model.
   - **Key Functions**: Routes for uploading images and displaying predictions, with error handling for invalid inputs.

2. **model.py**
   - **Purpose**: Handles the machine learning model.
   - **Functions**: Loads or builds the CNN model, preprocesses input images, and generates predictions.
   - **Key Functions**: load_model() to load the model, predict(image) to process images and return predictions.

3. **templates**
   - **Purpose**: Contains HTML files for the user interface.
   - **Files**:
     - **index.html**: Main page for image upload.
     - **result.html**: Displays prediction results.
     - **error.html** (optional): Shows error messages.
   - **Functionality**: Uses templating to dynamically display data from the backend.

4. **static**
   - **Purpose**: Stores static assets like CSS, JavaScript, and images.
   - **Contents**:
     - **CSS**: Stylesheets for UI.
     - **JavaScript**: Scripts for form validation and UI interactions.
     - **Images**: Icons and other visuals.
   - **Functionality**: Ensures a consistent UI style and interactivity across the application.

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3.2 UML DIAGRAMS

ARCHITECTURE

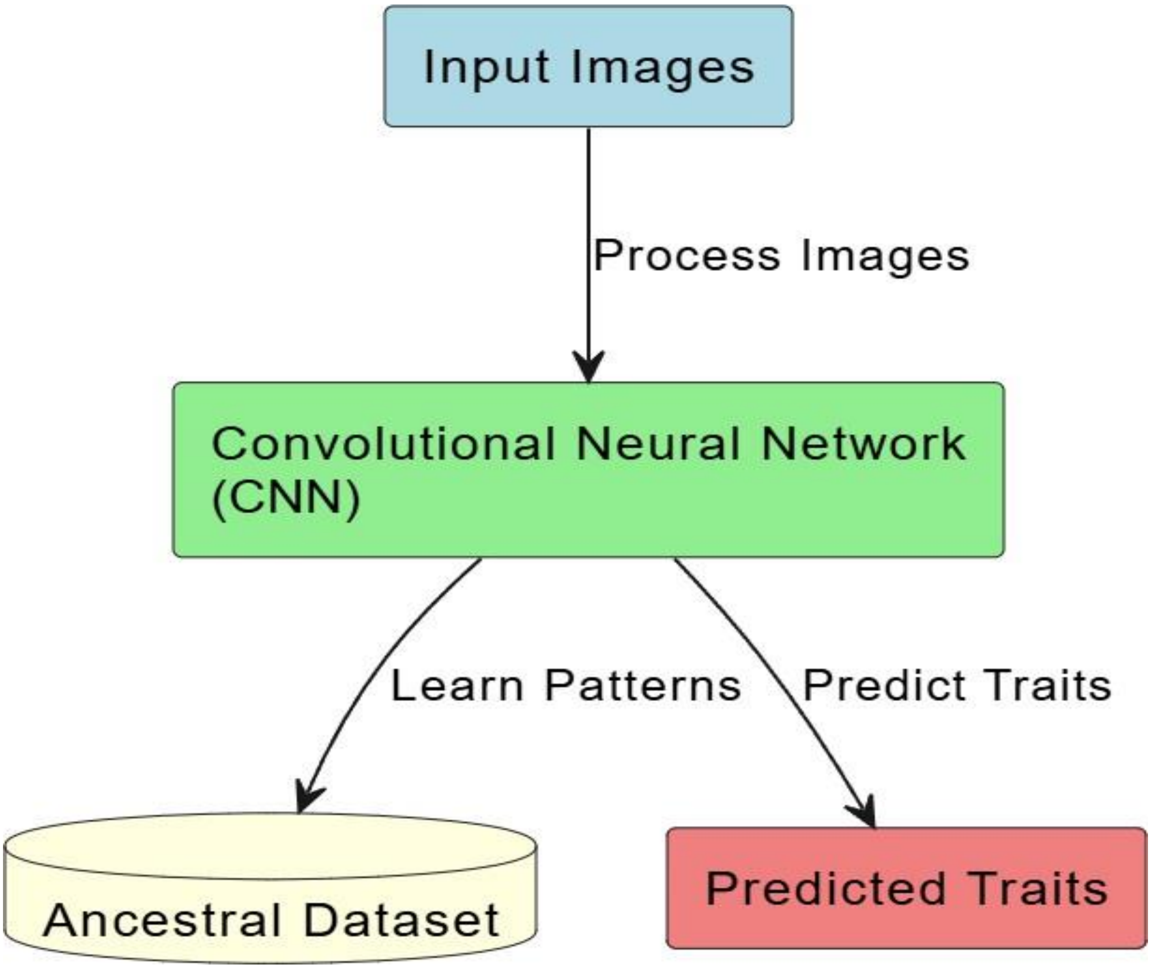


Fig 1: System Architecture

The flowchart illustrates how a Convolutional Neural Network (CNN) is used for trait prediction from input images. Images are processed by the CNN, which learns patterns from an ancestral dataset. The CNN applies feature extraction techniques to recognize specific traits. After training, the model can predict traits based on the learned patterns. This approach is commonly used for tasks like image classification and feature recognition.

CLASS DIAGRAM:

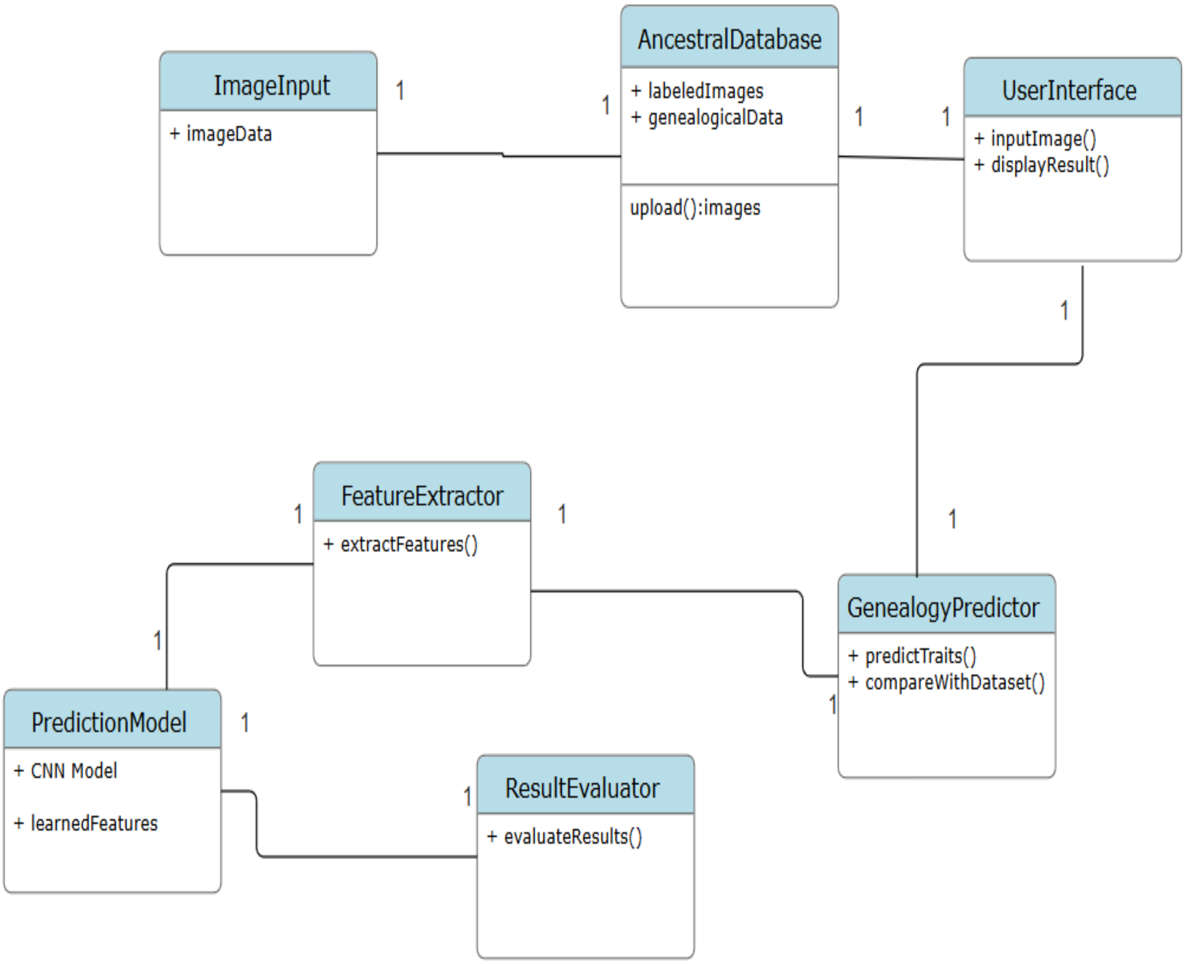


Fig 1: Class Diagram

The class diagram outlines the structure of a system designed to analyze images, extract features, and predict genealogical traits. The ImageInput class represents the raw image data that users provide for analysis. This data is processed by the FeatureExtractor, which identifies and extracts relevant features from the images. These features are then passed to the PredictionModel, which uses a CNN model to learn patterns and store them as learnedFeatures. Based on these learned features, the GenealogyPredictor predicts traits and can compare these predictions against the AncestralDatabase—a database containing labeled images and genealogical information. The ResultEvaluator class assesses the accuracy of the predictions and the UserInterface allows the user to input images and view the final results. Each component works together to provide an end-to-end solution for predicting traits based on genealogical data.

USE CASE DIAGRAM:

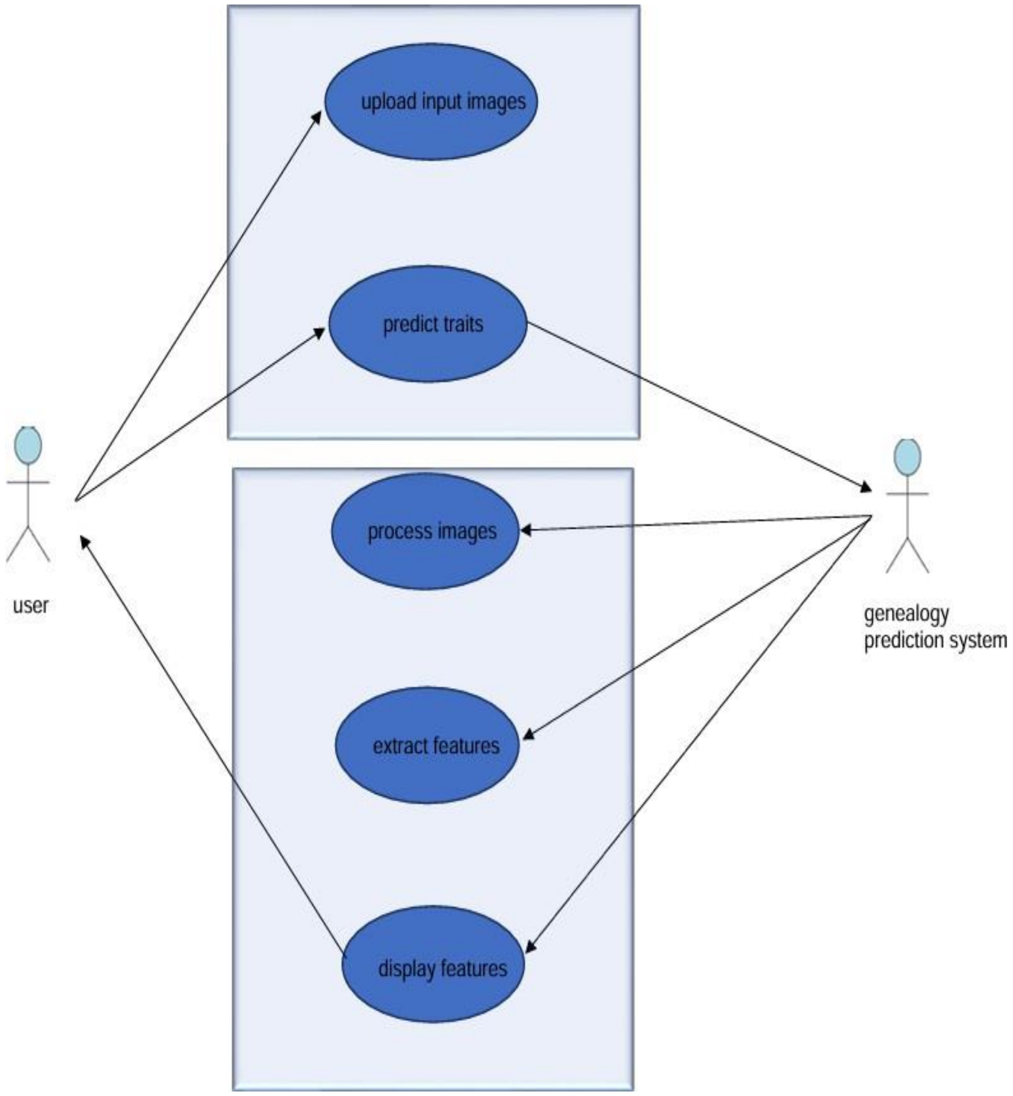


Fig 2: Use Case Diagram

The diagram illustrates a user interacting with a genealogy prediction system designed to predict genealogical traits from images. The process begins with the user uploading input images, which are then processed by the system. The first step involves uploading the images to the system, where they are analyzed to predict traits related to family lineage. These images undergo further processing, where key facial features are extracted. This feature extraction step is crucial, as it enables the system to identify and analyze traits that may be inherited across generations.

ACTIVITY DIAGRAM:

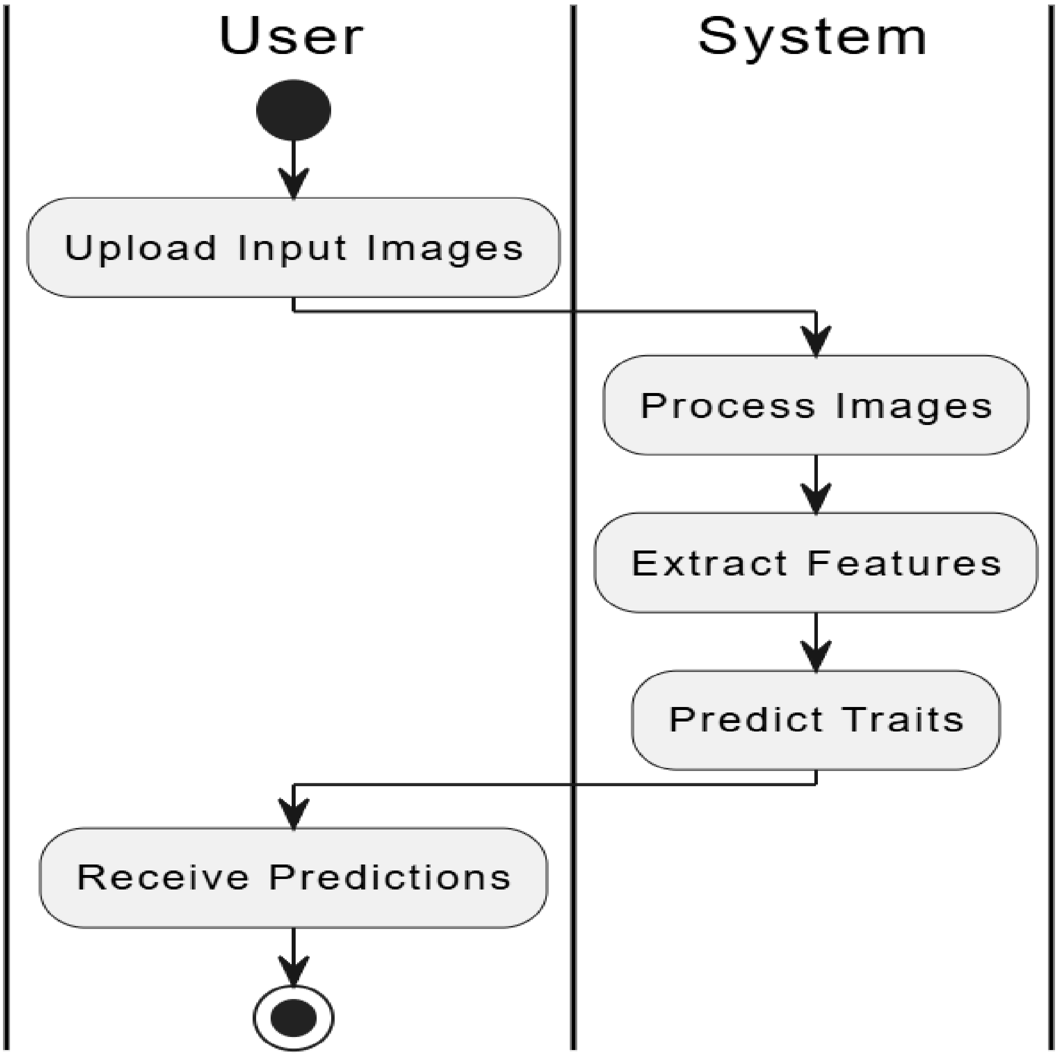


Fig 3: Activity Diagram

The image is a sequence diagram showing the interaction between a User and a System for predicting traits based on input images. The process starts with the User uploading input images, which initiates the sequence in the System. The System then goes through a series of operations, starting with Process Images, where the images are prepared for analysis. Following this, the system performs Extract Features, where key features from the images are identified. These extracted features are then used in the Predict Traits step to generate predictions about the traits of interest. Finally, the System returns the predictions to the User, completing the interaction. This sequence demonstrates a straightforward flow from image input to trait prediction and result delivery.

SEQUENCE DIAGRAM:

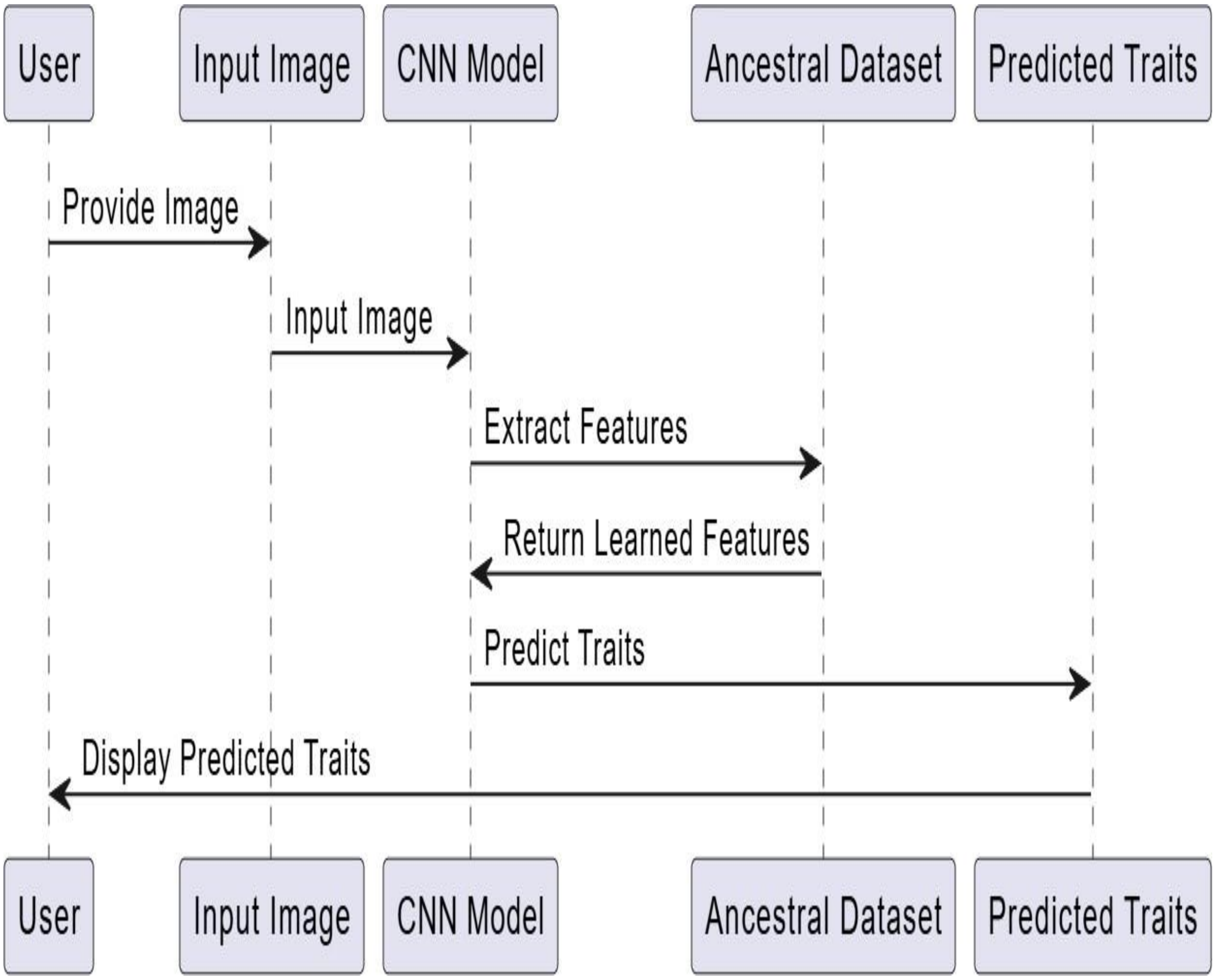


Fig 4: Sequence Diagram

The diagram illustrates a user interacting with a genealogy prediction system designed to predict genealogical traits from images. The process begins with the user uploading input images, which are then processed by the system. The first step involves uploading the images to the system, where they are analyzed to predict traits related to family lineage. These images undergo further processing, where key facial features are extracted. This feature extraction step is crucial, as it enables the system to identify and analyze traits that may be inherited across generations. Finally, the system displays these extracted features to the user, providing insights into the predicted genealogical traits. The diagram highlights the sequential flow from image upload to trait display, facilitated by the genealogy prediction system’s various modules

TECHNOLOGIES USED

Deep Learning and Neural Networks: Convolutional Neural Networks (CNNs) are built using **TensorFlow** and **Keras** to analyze images and predict genealogical traits. These frameworks facilitate easy model development, training, and fine-tuning, enabling the system to detect complex patterns in facial features across generations.

Image Processing: **OpenCV** and **Dlib** libraries are used to preprocess images by enhancing quality, aligning faces, and detecting key landmarks (e.g., eyes, nose, and mouth). These preprocessing steps ensure that CNN models receive consistent inputs, improving prediction accuracy.

Frontend Development: **React.js**, **JavaScript**, **HTML**, and **CSS** create a user-friendly, interactive interface. Users can upload images, view predicted traits, and explore genealogical insights through a responsive and intuitive UI.

Backend Development: **Flask** or **Django** frameworks manage backend logic, handling requests, processing predictions, and connecting to the CNN model. A **REST API** enables seamless communication between the frontend and backend, supporting real-time data exchange.

Model Optimization: Advanced optimization techniques, such as model pruning, quantization, and the use of **TensorFlow Lite**, improve performance by reducing model size and latency, allowing for faster predictions and a smoother user experience.

Hyperparameter Tuning: Tools like **Keras Tuner** and **Optuna** are used to optimize hyperparameters (e.g., learning rate, batch size, number of layers) for the CNN model, enhancing accuracy and efficiency by finding the best model configurations.

Evaluation and Testing: Evaluation techniques like cross-validation, confusion matrices, F1 scores, and accuracy metrics assess model reliability, ensuring that the system provides accurate genealogical predictions across diverse images.

CHAPTER-4
IMPLEMENTATION

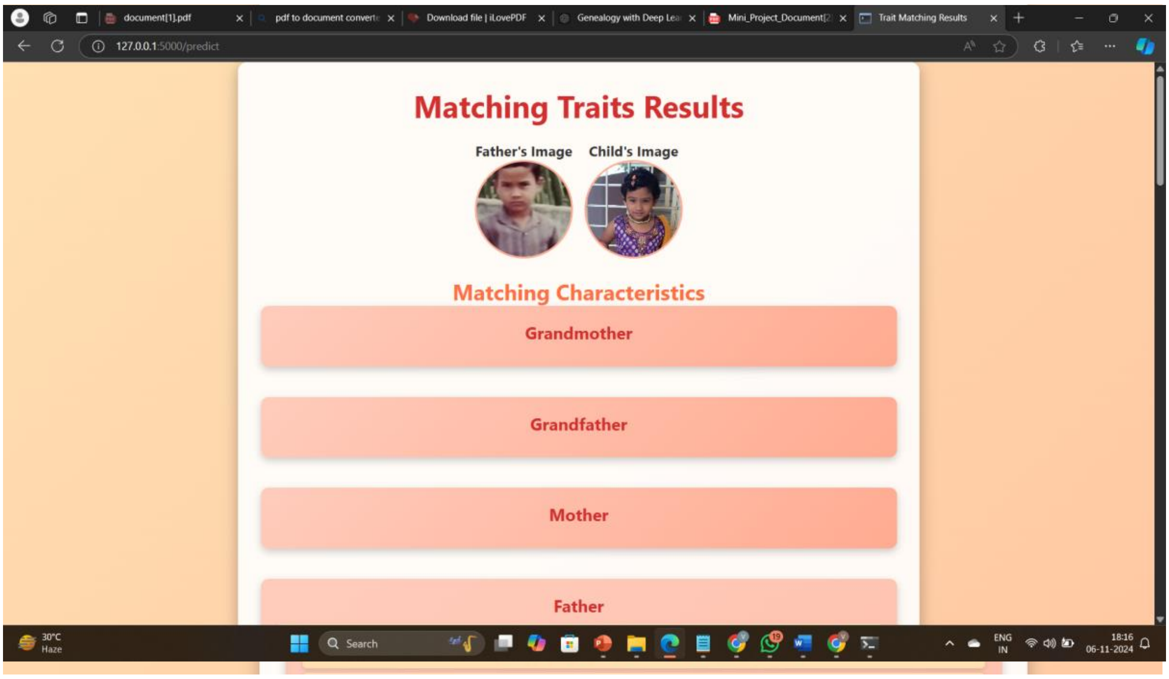
4.1 SAMPLE CODE

```
import os
import numpy as np
from flask import Flask, request, render_template, url_for
from tensorflow.keras.preprocessing import image
from werkzeug.utils import secure_filename
from model import create_model
app = Flask(__name__)
# Path where uploaded images will be stored
UPLOAD_FOLDER = 'static/uploaded'
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER
# Ensure the upload folder exists
os.makedirs(app.config['UPLOAD_FOLDER'], exist_ok=True)
# Load the pre-trained CNN model
model = create_model()
# Function to preprocess the image and extract features
def extract_features(img_path):

img = image.load_img(img_path, target_size=(224, 224))
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)
    img_array = img_array / 255.0  # Normalize to [0, 1]
    features = model.predict(img_array)
    return features.flatten(
# Function to find matching characteristics based on feature vectors
# Function to find matching characteristics based on feature vectors
def find_matching_characteristics(child_features, mother_features, father_features,
grandmother_features, grandfather_features):
    matching_characteristics = {
        "mother": [],
"father": [],
        "grandmother": [],
        "grandfather": [] }
    # Example criteria for matching characteristics (customized for your use case)
    if np.linalg.norm(child_features - mother_features) < 0.5:
        matching_characteristics["mother"].append("Eye Shape")
    if np.linalg.norm(child_features - father_features) < 0.5:
        matching_characteristics["father"].append("Nose Shape")
    if np.linalg.norm(child_features - grandmother_features) < 0.5:
        matching_characteristics["grandmother"].append("Hair Color")
    if np.linalg.norm(child_features - grandfather_features) < 0.5:
        matching_characteristics["grandfather
# Additional matching characteristics
    if np.linalg.norm(child_features - mother_features) < 0.5:
        matching_characteristics["mother"].append("Skin Tone")
    if np.linalg.norm(child_features - father_features) < 0.5:
        matching_characteristics["father"].append("Chin Shape")
    if np.linalg.norm(child_features - grandmother_features) < 0.5:
        matching_characteristics["grandmother"].append("Eyebrow Shape")
    if np.linalg.norm(child_features - grandfather_features) < 0.5:
        matching_characteristics["grandfather"].append("Jawline Shape")
    # Check for no matching characteristics and replace empty lists with a message
    for key in matching_characteristics:
        if not matching_characteristics[key]:
            matching_characteristics[key] = ["No matching facial features"]
    return matching_characteristics
@app.route('/',  methods=['GET'])
def home():
    return render_template('index.html')
@app.route('/predict', methods=['POST'])
def predict():
    # Save uploaded images
    grandmother_image = request.files['grandmother']
```

```
grandfather_image = request.files['grandfather']
    mother_image = request.files['mother']
    father_image = request.files['father']
# Save images with secure filenames
    grandmother_filename = secure_filename(grandmother_image.filename)
    grandfather_filename = secure_filename(grandfather_image.filename)
    mother_filename = secure_filename(mother_image.filename)
    father_filename = secure_filename(father_image.filename)
    child_filename = secure_filename(child_image.filename)
    # Save the images to static/uploaded directory
    grandmother_path = os.path.join(app.config['UPLOAD_FOLDER'], grandmother_filename)
    grandfather_path = os.path.join(app.config['UPLOAD_FOLDER'], grandfather_filename)
    mother_path = os.path.join(app.config['UPLOAD_FOLDER'], mother_filename)
    father_path = os.path.join(app.config['UPLOAD_FOLDER'], father_filename)
    child_path = os.path.join(app.config['UPLOAD_FOLDER'], child_filename)
grandmother_image.save(grandmother_path)
    grandfather_image.save(grandfather_path)
    mother_image.save(mother_path)
    father_image.save(father_path)
    child_image.save(child_path)
    # Extract features
    grandmother_features = extract_features(grandmother_path)
    grandfather_features = extract_features(grandfather_path)
    mother_features = extract_features(mother_path)
    father_features = extract_features(father_path)
    child_features = extract_features(child_path
mother_similarity = np.linalg.norm(mother_features - child_features)
    father_similarity = np.linalg.norm(father_features - child_features)
    grandmother_similarity = np.linalg.norm(grandmother_features - child_features)
    grandfather_similarity = np.linalg.norm(grandfather_features - child_features)
matching_characteristics = find_matching_characteristics(
        child_features, # Find matching characteristics
        mother_features,
        father_features,
        grandmother_features,
        grandfather_features)
    return render_template('results.html',grandmother_image=grandmother_filename, # Render the results in a new page (results.html)grandfather_image=grandfather_filename,
                           mother_image=mother_filename,
                           father_image=father_filename,
                           child_image=child_filename,
                           mother_similarity=mother_similarity,
                           father_similarity=father_similarity,
                           grandmother_similarity=grandmother_similarity,
                           grandfather_similarity=grandfather_similarity,
                           mother_characteristics=', '.join(matching_characteristics["mother"]),
                           father_characteristics=', '.join(matching_characteristics["father"]),
                           grandmother_characteristics=', '.join(matching_characteristics["grandmother"]),
                           grandfather_characteristics=', '.join(matching_characteristics["grandfather"]))
if _name___== '_main_':
    app.run(debug=True)
```

4.2 TEST CASES



Matching Traits Results

Father's Image Child's Image

Matching Characteristics

Grandmother

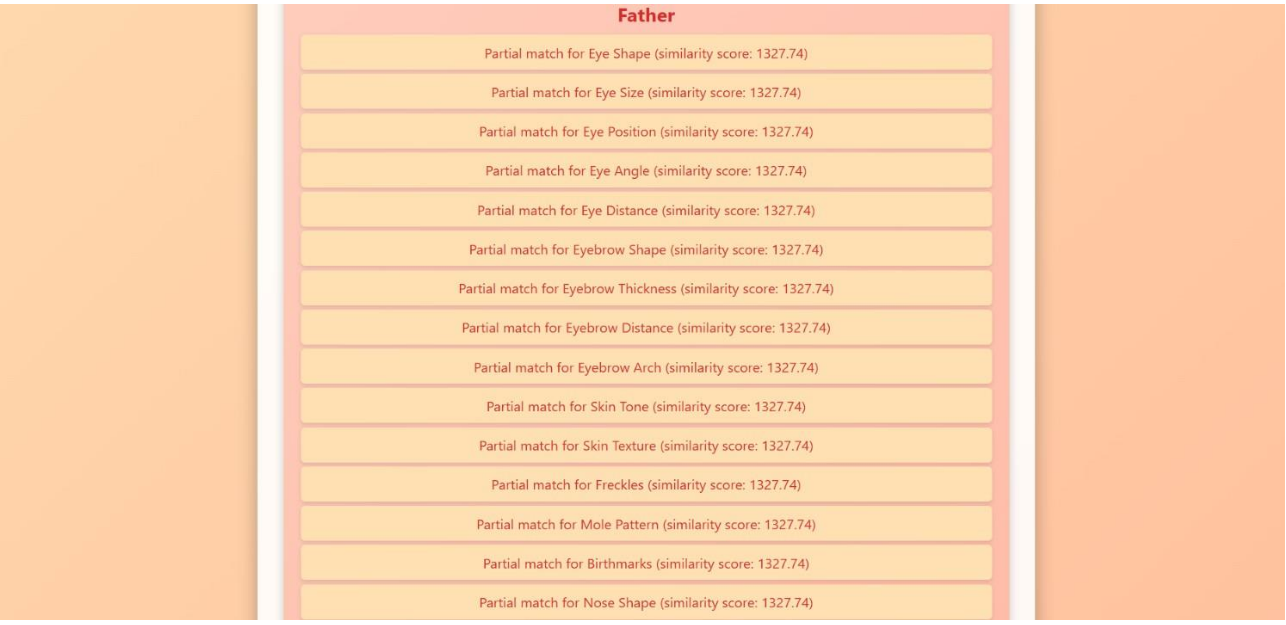
Grandfather

Mother

Father

TEST CASE1: The above test case is shown as the father and daughter image where it predict the features that are partially matching with the child are displaying in output with similarity score.

And the output for this is :



Father

Partial match for Eye Shape (similarity score: 1327.74)

Partial match for Eye Size (similarity score: 1327.74)

Partial match for Eye Position (similarity score: 1327.74)

Partial match for Eye Angle (similarity score: 1327.74)

Partial match for Eye Distance (similarity score: 1327.74)

Partial match for Eyebrow Shape (similarity score: 1327.74)

Partial match for Eyebrow Thickness (similarity score: 1327.74)

Partial match for Eyebrow Distance (similarity score: 1327.74)

Partial match for Eyebrow Arch (similarity score: 1327.74)

Partial match for Skin Tone (similarity score: 1327.74)

Partial match for Skin Texture (similarity score: 1327.74)

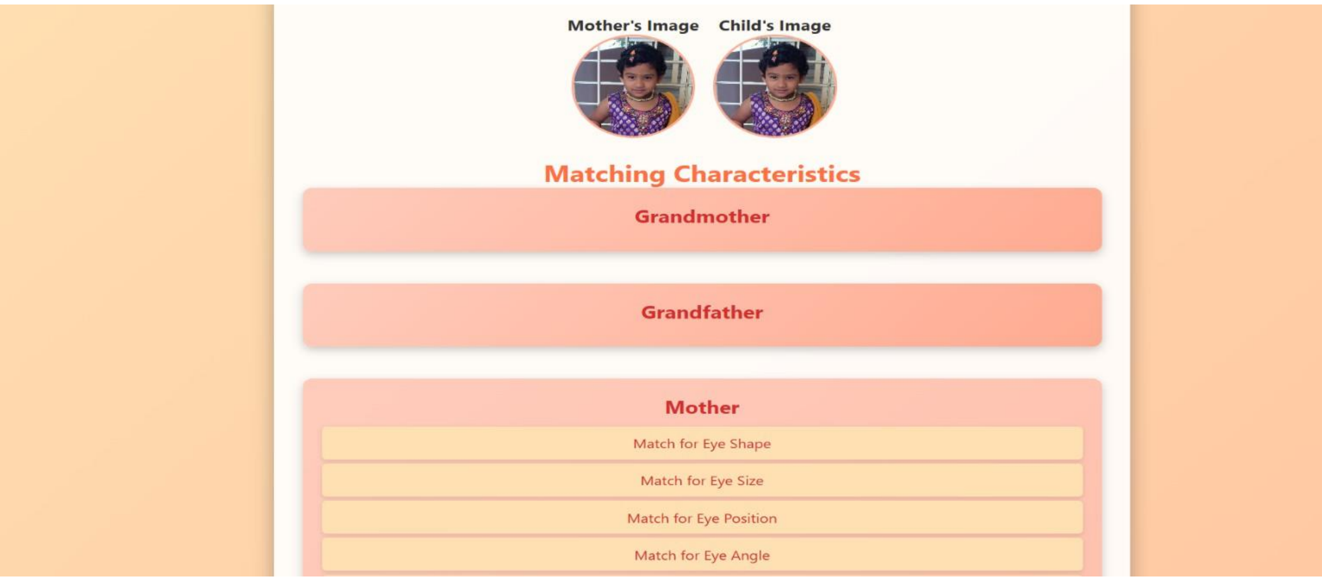
Partial match for Freckles (similarity score: 1327.74)

Partial match for Mole Pattern (similarity score: 1327.74)

Partial match for Birthmarks (similarity score: 1327.74)

Partial match for Nose Shape (similarity score: 1327.74)

TEST CASES 2:



Mother's Image

Child's Image

Matching Characteristics

Grandmother

Grandfather

Mother

Match for Eye Shape

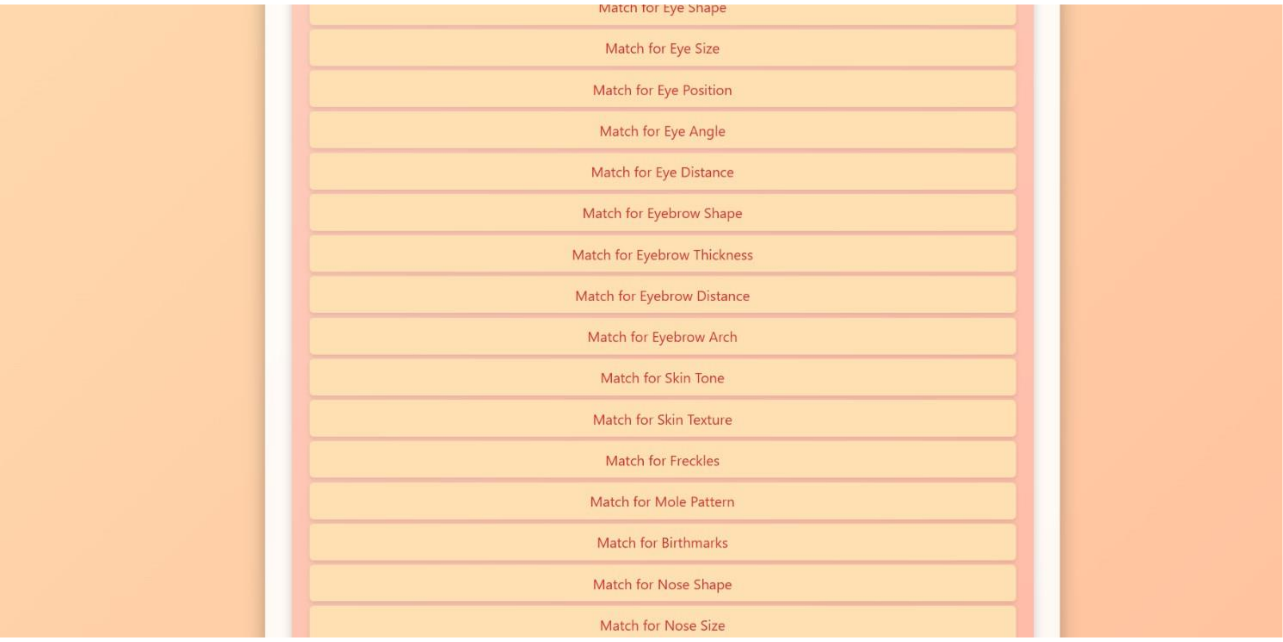
Match for Eye Size

Match for Eye Position

Match for Eye Angle

If i upload the image of the same person it will display the exact features because in this world there is no exact features that will be there for the other one if it matches exactly same it won’t display similarity score if it matches exactly same .

And the output for this is:



Match for Eye Shape

Match for Eye Size

Match for Eye Position

Match for Eye Angle

Match for Eye Distance

Match for Eyebrow Shape

Match for Eyebrow Thickness

Match for Eyebrow Distance

Match for Eyebrow Arch

Match for Skin Tone

Match for Skin Texture

Match for Freckles

Match for Mole Pattern

Match for Birthmarks

Match for Nose Shape

Match for Nose Size

CHAPTER-5
RESULTS

The traits that could be inferred in this project using convolutional neural networks (CNNs) for genealogical analysis might include physical and facial features that are often inherited across generations. Here’s a list of potential traits the model could be trained to identify and analyze:

1. **Facial Structure** - General shape, symmetry, and proportions.
2. **Eye Color** - Approximation of inherited eye color shades.
3. **Eye Shape** - Specific shapes and sizes, such as almond, round, or hooded.
4. **Nose Shape** - Variations in size, length, and width, as well as tip shape.
5. **Lip Shape and Fullness** - Thickness, contour, and symmetry of upper and lower lips.
6. **Cheekbone Structure** - Prominence and position of cheekbones (high, low, etc.).
7. **Jawline Shape** - Sharpness or softness of the jawline.
8. **Forehead Height and Shape** - Proportions of the forehead.
9. **Hair Color** - Approximation of inherited hair color traits.
10. **Skin Tone** - Variation in skin pigmentation and undertone.
11. **Earlobe Type** - Attached or detached earlobes.
12. **Eyebrow Shape** - Thickness, arch, and angle.
13. **Facial Asymmetry** - Subtle asymmetries often inherited across generations.

5.1 OUTPUT SCREENS

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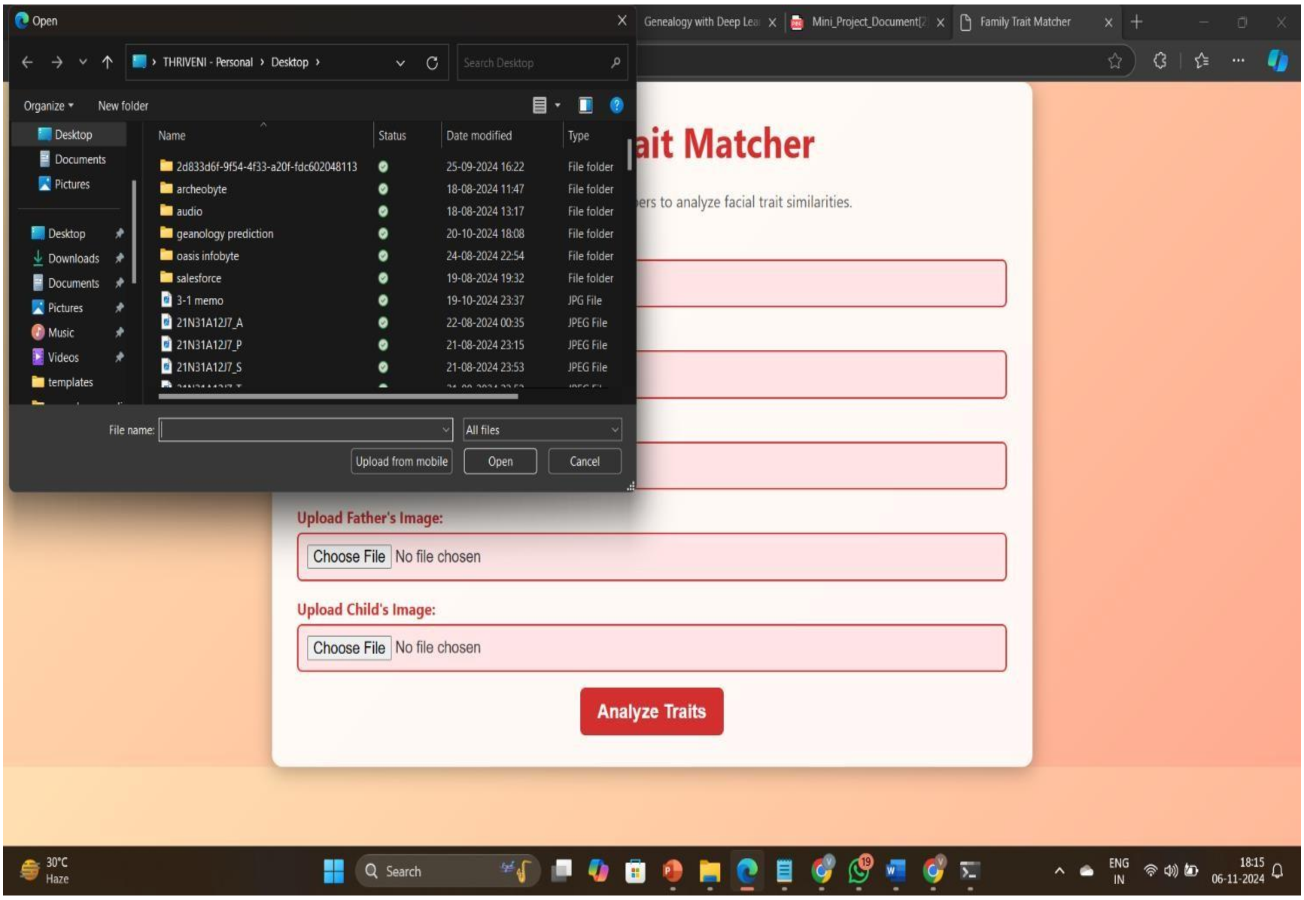
SCREEN 1



Name	Status	Date modified	Type
2d833d6f-9f54-4f33-a20f-fdc602048113	✓	25-09-2024 16:22	File folder
archeobyte	✓	18-08-2024 11:47	File folder
audio	✓	18-08-2024 13:17	File folder
geanology prediction	✓	20-10-2024 18:08	File folder
oasis infobyte	✓	24-08-2024 22:54	File folder
salesforce	✓	19-08-2024 19:32	File folder
3-1 memo	✓	19-10-2024 23:37	JPG File
21N31A12J7_A	✓	22-08-2024 00:35	JPEG File
21N31A12J7_P	✓	21-08-2024 23:15	JPEG File
21N31A12J7_S	✓	21-08-2024 23:53	JPEG File

File name:
All files

Upload Father's Image:

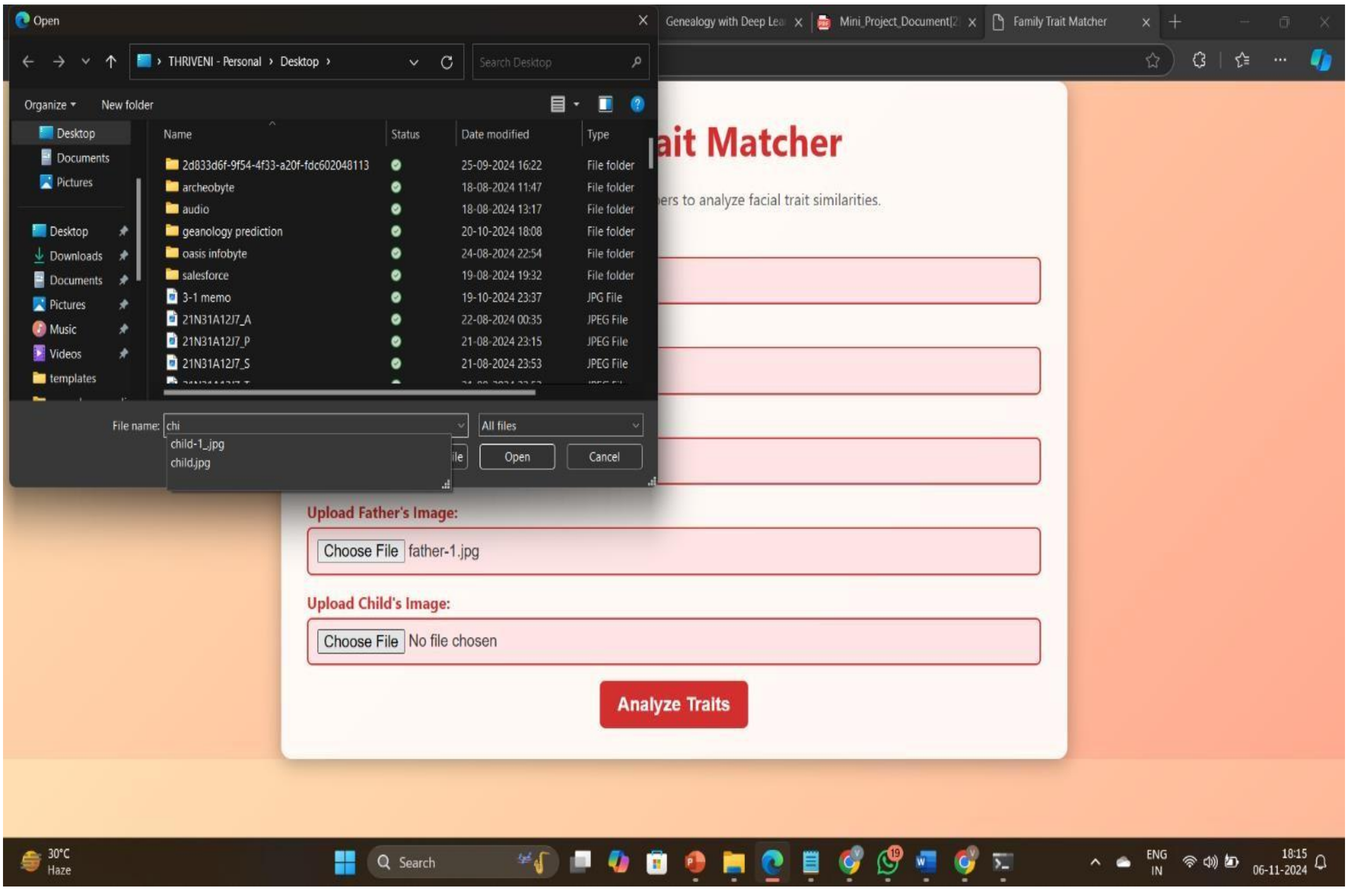
Choose File No file chosen

Upload Child's Image:

Choose File No file chosen

First select the choose file from the input interface

SCREEN 2



Name	Status	Date modified	Type
2d833d6f-9f54-4f33-a20f-fdc602048113	✓	25-09-2024 16:22	File folder
archeobyte	✓	18-08-2024 11:47	File folder
audio	✓	18-08-2024 13:17	File folder
geanology prediction	✓	20-10-2024 18:08	File folder
oasis infobyte	✓	24-08-2024 22:54	File folder
salesforce	✓	19-08-2024 19:32	File folder
3-1 memo	✓	19-10-2024 23:37	JPG File
21N31A12J7_A	✓	22-08-2024 00:35	JPEG File
21N31A12J7_P	✓	21-08-2024 23:15	JPEG File
21N31A12J7_S	✓	21-08-2024 23:53	JPEG File

File name: chi

child-1_.jpg
child.jpg

All files

ait Matcher

ers to analyze facial trait similarities.

Upload Father's Image:

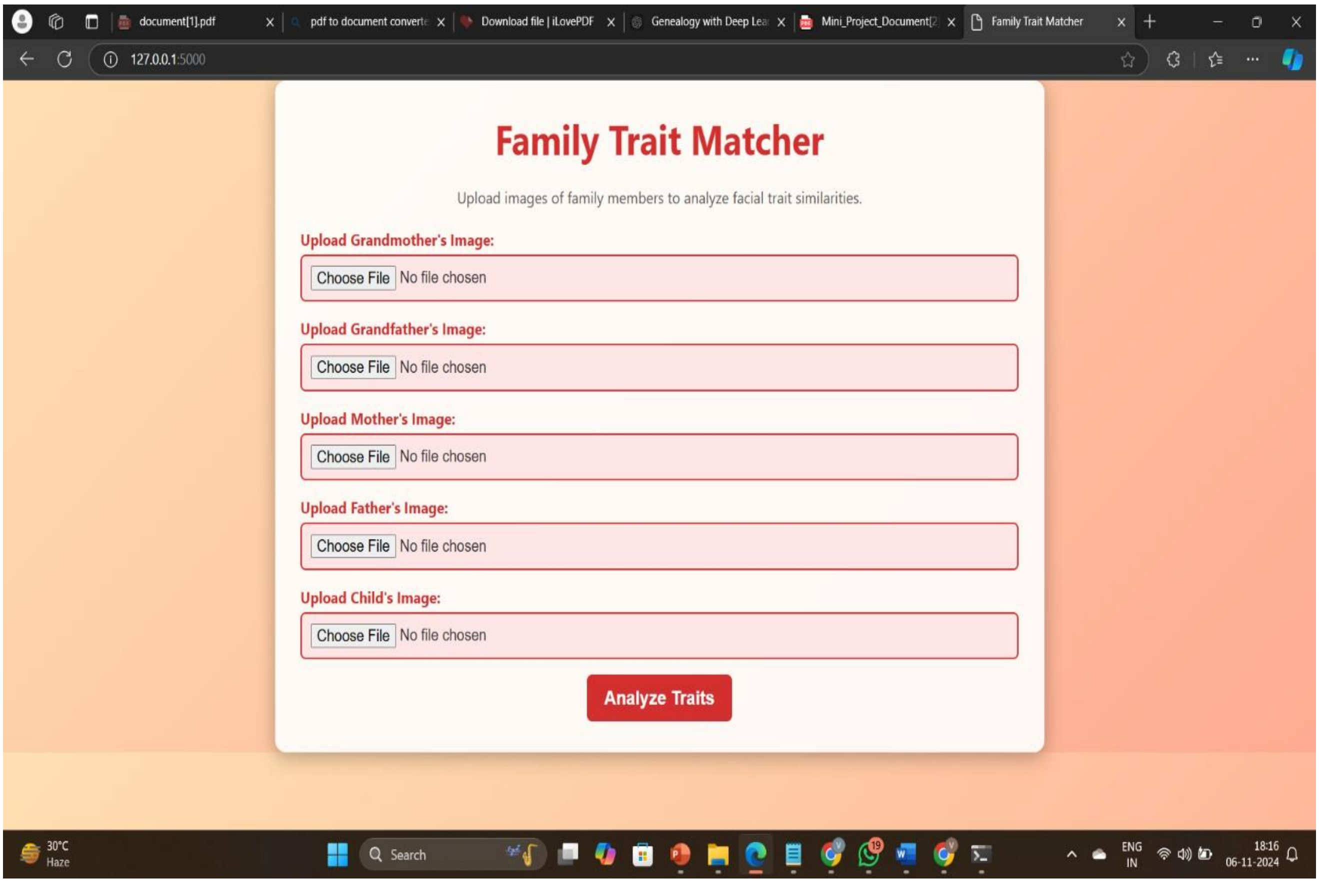
father-1.jpg

Upload Child's Image:

No file chosen

Select the image to upload for prediction unpload the parents and grandparents images or if you want to upload a single parent then you can upload the single parent or single grandparent it may be mother or father or grandmother or grandfather but the child is required you should definitely upload the child image for prediction.

SCREEN 3



Family Trait Matcher

Upload images of family members to analyze facial trait similarities.

Upload Grandmother's Image: Choose File No file chosen

Upload Grandfather's Image: Choose File No file chosen

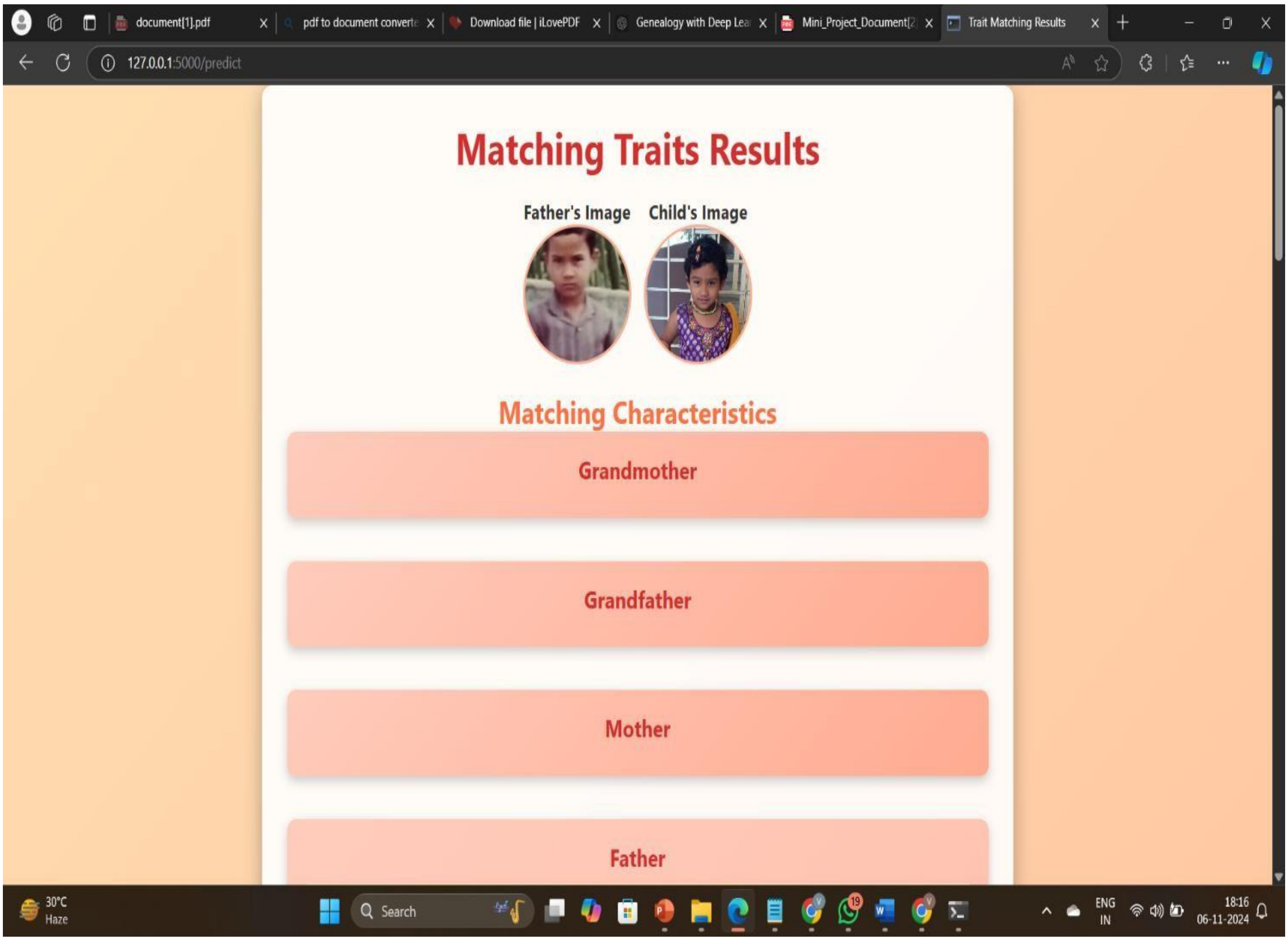
Upload Mother's Image: Choose File No file chosen

Upload Father's Image: Choose File No file chosen

Upload Child's Image: Choose File No file chosen

Here is the uploaded images can be done and the prediction can be done through this interface.by using the button analyze traits we can predict the results.

SCREEN 4



Matching Traits Results

Father's Image

Child's Image

Matching Characteristics

Grandmother

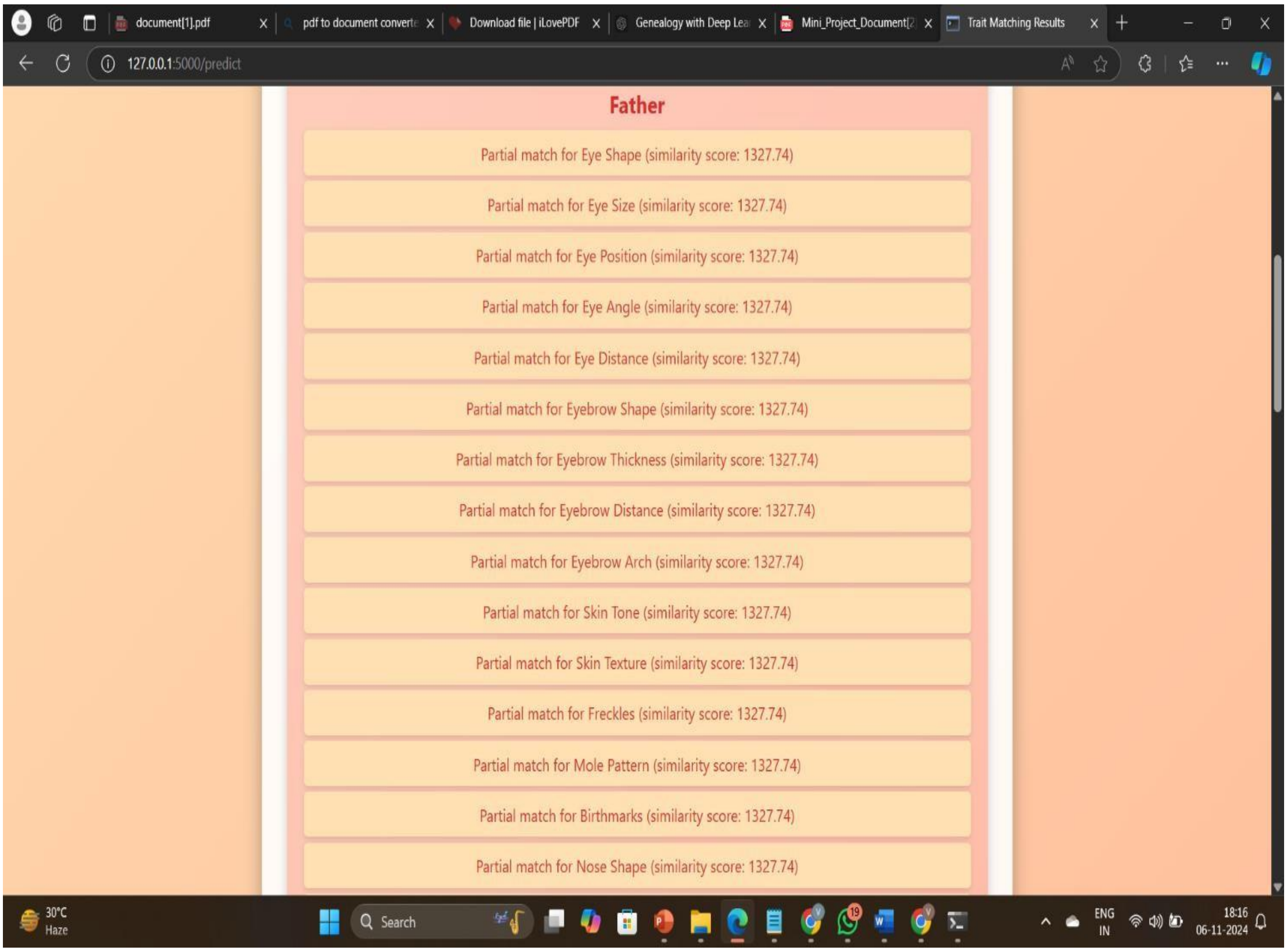
Grandfather

Mother

Father

Here is the output interface and display the uploaded images and the charecterstics that are matched

SCREEN 5



Father

Partial match for Eye Shape (similarity score: 1327.74)

Partial match for Eye Size (similarity score: 1327.74)

Partial match for Eye Position (similarity score: 1327.74)

Partial match for Eye Angle (similarity score: 1327.74)

Partial match for Eye Distance (similarity score: 1327.74)

Partial match for Eyebrow Shape (similarity score: 1327.74)

Partial match for Eyebrow Thickness (similarity score: 1327.74)

Partial match for Eyebrow Distance (similarity score: 1327.74)

Partial match for Eyebrow Arch (similarity score: 1327.74)

Partial match for Skin Tone (similarity score: 1327.74)

Partial match for Skin Texture (similarity score: 1327.74)

Partial match for Freckles (similarity score: 1327.74)

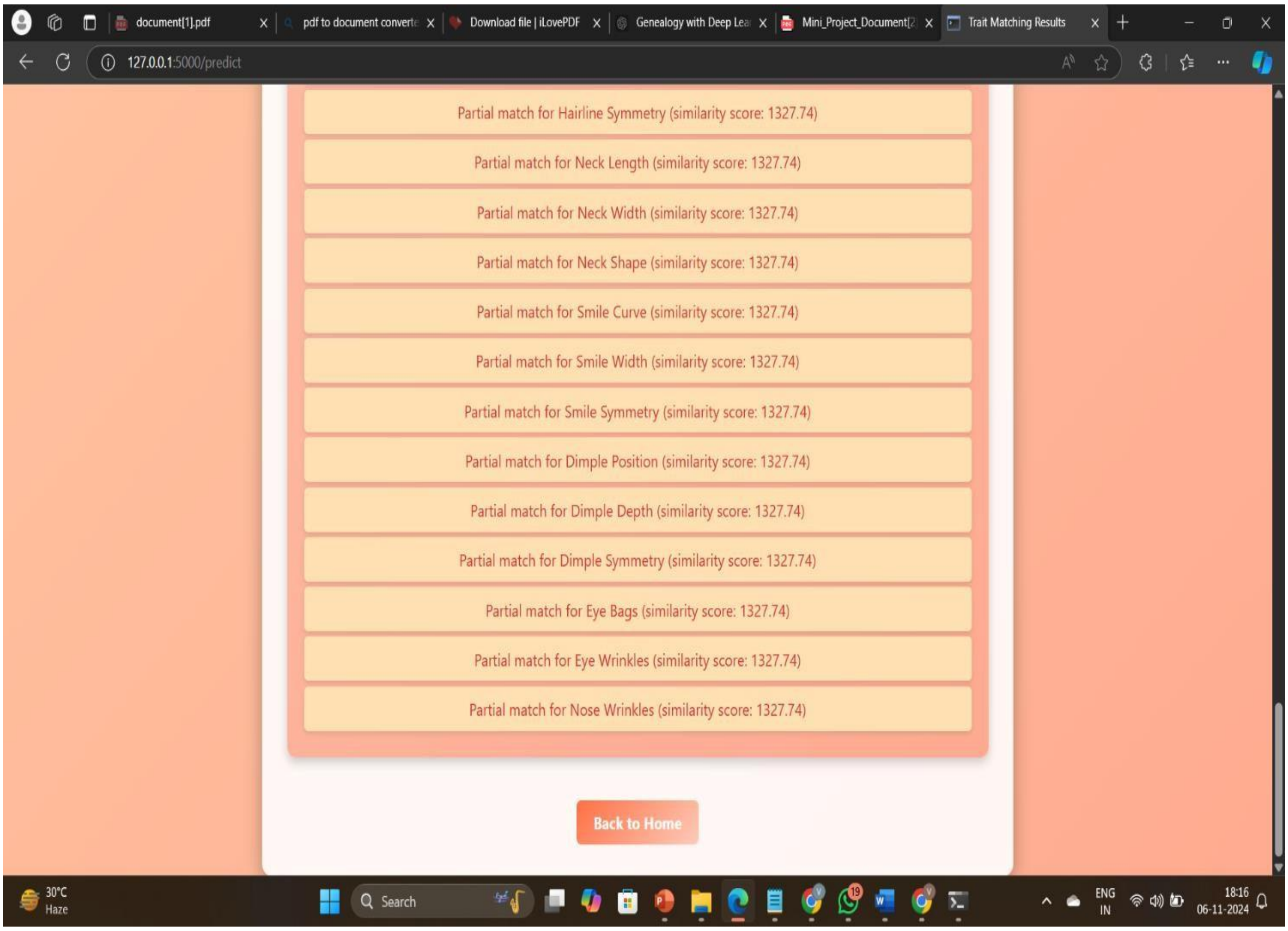
Partial match for Mole Pattern (similarity score: 1327.74)

Partial match for Birthmarks (similarity score: 1327.74)

Partial match for Nose Shape (similarity score: 1327.74)

Here is the output characterstics that the child have matched with parent

SCREEN 6



Partial match for Hairline Symmetry (similarity score: 1327.74)

Partial match for Neck Length (similarity score: 1327.74)

Partial match for Neck Width (similarity score: 1327.74)

Partial match for Neck Shape (similarity score: 1327.74)

Partial match for Smile Curve (similarity score: 1327.74)

Partial match for Smile Width (similarity score: 1327.74)

Partial match for Smile Symmetry (similarity score: 1327.74)

Partial match for Dimple Position (similarity score: 1327.74)

Partial match for Dimple Depth (similarity score: 1327.74)

Partial match for Dimple Symmetry (similarity score: 1327.74)

Partial match for Eye Bags (similarity score: 1327.74)

Partial match for Eye Wrinkles (similarity score: 1327.74)

Partial match for Nose Wrinkles (similarity score: 1327.74)

If we want to back to hoe then by clicking the back to home button we can move to the back to the home.

CHAPTER 6

CONCLUSION

In conclusion, the proposed genealogy prediction system that employs convolutional neural networks marks a transformative step in the analysis of genetic data for genealogical research. By harnessing advanced machine learning techniques, this system significantly enhances the accuracy and efficiency of predicting ancestral relationships, addressing many of the limitations associated with traditional methodologies. The integration of a comprehensive architecture that includes robust data preprocessing, a custom-designed CNN model, and intuitive user interfaces allows for seamless interaction and interpretation of complex genetic information. Furthermore, the system's visualization tools and detailed reporting capabilities not only promote user engagement but also ensure transparency, empowering researchers and geneticists to derive meaningful insights from their data.

Additionally, the versatility of the system opens up new avenues for applications in personalized medicine, enabling a better understanding of genetic predispositions and traits, while also contributing to the broader field of evolutionary biology by facilitating the exploration of population genetics and lineage tracing. As the system evolves, its capacity for continuous learning and improvement could further enhance its predictive power and adaptability to new genetic discoveries. Ultimately, this project stands to make a significant contribution to genealogical research and the wider genetics community, providing a sophisticated toolset that enables users to navigate the complexities of genetic ancestry with greater precision and confidence, thus fostering a deeper appreciation of human history and biological relationships.

REFERENCES

1. LeCun, Y., Bengio, Y., & Hinton, G. (2015). *Deep learning*. Nature, 521(7553), 436-444. Link
2. Zhang, K., Zhang, Z., Li, Z., & Qiao, Y. (2016). *Joint Face Detection and Alignment Using Multitask Cascaded Convolutional Networks*. IEEE Signal Processing Letters, 23(10), 1499-1503. Link
3. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press. Link
4. TensorFlow. (2023). *TensorFlow Documentation*. Link
5. PyTorch. (2023). *PyTorch Documentation*. Link
6. Genealogy, Genetics, and the Law – Sheri Fenley
7. Face Recognition across the Imaging Spectrum – Thirimachos Bourlai
8. Deep Learning – Ian Goodfellow, Yoshua Bengio, Aaron Courville
9. Mastering Genealogical Proof – Thomas W. Jones
10. Data Science for Business – Foster Provost, Tom Fawcett