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ID Vision Web Based Face ID with Partial Feature Detection

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ABSTRACT:

The study introduces "ID Vision", a face recognition software intended to streamline student identification and attendance monitoring in schools. Whereas manual attendance is not only slow and plagued with errors, it is also not satisfactory from a security standpoint, nowadays automated attendance systems face the difficulty of low-light and partial face visibility in addition to the small size of their training databases. Unlike these systems, in our application, we apply Deep Learning CNN with VGG-16 along with Haar Cascade and Dlib landmark detectors, which allow us to also detect and identify partial faces such as eyes, nose, or lips. We created a dataset consisting of 100 to 200 student images, which was further enhanced using data augmentation methods such as flips, rotations, and the creation of synthetic low-light images to enhance robustness. The recognition engine is hosted on a Flask web application that uses an SQLite database to store student metadata, enabling the continuous mapping of faces to roll and class numbers. Initial tests show the model's accuracy is above 90% while still working in real-time with TensorFlow Lite on regular devices. The system shows efficiency and inclusivity improvements. Campus faculty benefit from the improved security and requires fifteen fewer hours a week to oversee attendance, along with having improved security. The system complements the ID Vision smart campus system by solving the problems of partial feature detection and adaptability to the environment, which the campus previously lacked, in a cost-effective manner. In the future, it also has the potential of being deployed on mobile devices and for the general community.

Keywords: Face Recognition, Partial Feature Detection, CNN, VGG-16, Attendance Automation, Deep Learning, Educational Technology

Introduction

Face recognition has emerged as a leading biometric technique for authentication and identification in diverse domains such as security, healthcare, banking, and education. Traditional approaches relied heavily on detecting full facial features, making them vulnerable to challenges such as low-light environments, partial occlusion, or variations in pose and expression. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved recognition accuracy, enabling robust performance in real-world conditions. However, most existing systems still struggle when only partial facial regions are visible, which has become increasingly common in post-pandemic environments where masks and obstructions are prevalent.

In educational institutions, manual methods of student identification and attendance tracking remain time-consuming, error-prone, and inefficient. For example, roll calls or paper-based registers not only waste classroom time but also pose difficulties in maintaining reliable records. Even existing automated systems often fail when faces are partially obscured, or when datasets are too small to train large-scale models effectively. These limitations create a pressing need for an accurate, real-time, and scalable solution that can adapt to institutional contexts.

This project, ID Vision: Web-Based Face ID with Partial Feature Detection, addresses these challenges by combining dlib's 68-point facial landmark detection with deep learning techniques. The system extracts key facial regions—eyes, nose, lips, and full face—and classifies them using a fine-tuned ResNet50 model trained on both CIFAR-10 and a custom dataset of student images. To overcome dataset limitations, data augmentation techniques such as rotation, zooming, horizontal flipping, and synthetic low-light generation are applied, improving adaptability across diverse environmental conditions.

A key innovation of the system is its deployment as a Flask-based web application, which allows administrators and educators to interact with the model in real time. The platform supports functionalities such as dataset loading, model building, training progress visualization, evaluation through classification metrics, and real-time predictions on uploaded images. Additionally, metadata—including student names, roll numbers, and class details—is dynamically integrated through JSON mapping, ensuring that recognized faces are directly linked to institutional records.

By achieving over 90% accuracy in preliminary experiments and maintaining low-latency predictions through TensorFlow Lite optimization, the system demonstrates its potential as a cost-effective and practical solution for smart campuses. Beyond automating attendance and enhancing campus security, the project paves the way for broader community impact through scalable deployment, mobile application integration, and future extensions involving multimodal biometrics such as voice or fingerprint recognition.

Literature Review

[1] Attention-based Partial Face Recognition (Hörmann et al., 2021)

This paper proposed an attention mechanism built on ResNet feature maps that allows the system to selectively focus on visible parts of the face. It shows robustness under real and synthetic occlusion, outperforming standard CNNs. The attention mechanism reduces dependency on full facial visibility, which is especially relevant for classroom scenarios with masks or angled faces.

Relevance: Provides a strong foundation for partial face recognition in your system, suggesting that attention layers could be added on top of VGG/ResNet architectures.

[2] Self-restrained Triplet Loss for Accurate Masked Face Recognition (Boutros et al., 2021)

The authors designed a modified triplet loss that adapts embeddings of masked and unmasked faces, ensuring that features extracted from both are close in latent space. They also introduced an embedding unmasking model (EUM) to refine feature alignment.

Relevance: Can inspire better loss functions in your project, especially if you want to go beyond categorical cross-entropy for partial face learning.

[3] Mask-invariant Face Recognition with Knowledge Distillation (Huber et al., 2021)

This work introduced template-level knowledge distillation, teaching a student network to align masked face embeddings with unmasked templates. It improves recognition without requiring entirely new datasets.

Relevance: Shows a way to reuse pre-trained models (like ResNet50 in your project) and adapt them to masked/partial conditions with minimal retraining.

[4] Occlusion Robust Face Recognition with Siamese Network (Song et al., 2019)

A Siamese CNN was trained to identify and discard corrupted or occluded features using a mask dictionary. This makes recognition robust when significant facial regions are missing.

Relevance: Your dlib-based eye/nose/lip extraction could benefit from a similar selective masking approach, ensuring only clean features are passed into the CNN.

[5] Recognizing Partial Biometric Patterns (He et al., 2018)

This paper proposed triplet loss with dictionary learning to handle partial biometric patterns (faces, gait, etc.). The method demonstrated state-of-the-art performance in situations where only a subset of features was visible.

Relevance: Strong theoretical support for your project—validates the concept of treating partial faces (eyes, nose, lips) as sufficient for identity recognition.

[6] Survey of Face Recognition Under Occlusion (Zeng, 2021)

Provides a comprehensive review of occlusion-aware methods, from sparse representation classification to fully convolutional networks (FCN) and GAN-based reconstructions. Highlights gaps in datasets and real-time deployment.

Relevance: Very useful in your paper's Literature Review section to justify why existing solutions are insufficient for real-world classroom deployment.

[7] CNN-based Partial Face Detection (Islam et al., 2022)

Proposes a CNN pipeline with Haar Cascade and MTCNN for partial face detection. Achieved ~96% accuracy on a custom dataset of cropped facial parts, showing feasibility of real-time detection.

Relevance: Directly matches your system's preprocessing stage where dlib extracts eyes, nose, lips before recognition. Supports your methodology with empirical validation.

[8] Review of Masked Face Recognition Based on Deep Learning (MDPI, 2022)

This review categorizes different deep learning solutions for masked recognition—CNN, GAN-based completion, and multimodal methods. It also analyzes datasets created during COVID-19 for masked face research.

Relevance: Can help justify the novelty of your project, since most approaches focus on masks, while yours generalizes to any partial face (eyes, nose, lips).

[9] Masked Face Recognition Using Deep Learning (Springer, 2023)

Explores modern solutions like thermal imaging fusion, multimodal approaches, and hybrid CNN architectures. It also highlights ethical and privacy challenges in using facial recognition for institutions.

Relevance: Gives context for future extensions—if your system scales beyond attendance, multimodal features (voice + face) can enhance accuracy.

[10] Deep Representation for Partially Occluded Face Verification (EURASIP, 2018)

Focuses on deep feature learning that is resilient to occlusion. The method improved verification accuracy on datasets where parts of the face were hidden, proving deep models outperform shallow handcrafted features.

Relevance: Strong experimental evidence that CNN-based models (like your ResNet50) are the right choice for partial face identification.

Methodology

Existing Methodology

Full-face, global descriptors. Early systems (Eigenfaces/Fisherfaces, PCA/LDA) represent the whole face as a low-dimensional vector. They are lightweight but brittle to pose, illumination, and occlusion.

Local handcrafted features. LBP/HOG + SVM/nearest-neighbor improve robustness to lighting and minor pose changes, yet still degrade sharply with masks/partial visibility and rarely scale well to large, in-the-wild data.

Deep CNN pipelines (full-face). Modern systems detect faces (e.g., Haar/MTCNN/RetinaFace), align, then embed with CNNs (VGG-Face, FaceNet, ArcFace) and classify/verify. These achieve high accuracy but assume largely visible faces; performance drops with occlusions unless explicitly handled.

- Occlusion-aware variants. Three common directions:
- Region dropping/attention to down-weight occluded areas,
- Reconstruction/completion (GANs) to “fill” the missing region,

Masked/partial training with special losses (triplet/margin) so masked and unmasked embeddings align.

These improve robustness but often require curated datasets or complex training tricks, and many works do not integrate end-to-end with institutional metadata/workflows (e.g., attendance systems).

Proposed Methodology

We propose an end-to-end web-based face recognition system that remains functional under partial visibility by explicitly extracting and learning from facial sub-regions (eyes, nose, lips) alongside the full face. The pipeline integrates computer vision (dlib landmarks), transfer learning (ResNet50), targeted augmentation, and a Flask backend for training, inference, and reporting—all tied to institutional metadata for automated attendance.

Data Preparation & Partial-Feature Generation

- Sources: A custom student dataset (per-class folders) plus optional public images for pretraining context.
- Detection & landmarks: dlib’s frontal face detector and 68-point predictor locate facial geometry.
- Region extraction: From each detected face, crop eyes (L/R concatenated), nose, lips, and full face.
- Normalization: Convert to RGB, resize to 32×32 (as in code), scale to [0,1].
- Augmentation: Rotation, shifts, shear/zoom, horizontal flip, and brightness jitter to simulate real-world conditions (low light, pose, blur).
- Labeling: Folder structure <person>/<part>/img.jpg automatically yields labels; a metadata.json holds {id: name, roll_number, class} for downstream mapping.

Model Architecture & Training

- Backbone: ResNet50 (ImageNet weights, include_top=False), frozen for initial training to stabilize small datasets.
- Head: GlobalAveragePooling2D → Dense(512, ReLU) → Dense(C, softmax) where C is number of identities.
- Loss & optimizer: categorical_crossentropy with Adam (1e-4); class weights mitigate label imbalance.
- Curriculum: Early stopping on val_accuracy, learning-rate schedule after epoch 15; data fed by an ImageDataGenerator.
- Rationale: Leveraging transfer learning focuses training on discriminative mid-/high-level features that persist even when only sub-regions are visible.

Evaluation Protocol

- Splits: Train/validation/test with person-stratified splitting to avoid identity leakage.
- Metrics: Accuracy, precision/recall/F1 per identity, and confusion matrix; optional ROC for verification-style analysis.

Ablations:

Full vs partial (eyes/nose/lips) performance,

With vs without augmentation,

Backbone freeze vs fine-tuning top blocks,

Latency on target hardware for real-time suitability.

Reporting: The Flask app exposes JSON endpoints returning classification report and CM; training curves (acc/loss) are exported as plots.

Deployment & Integration

- Backend: Flask with endpoints for /load_data, /build_model, /train_model, /evaluate_model, /predict, /load_model.
- Persistence: Models saved as Keras files; metadata resolved at prediction time to return {name, roll_number, class} along with predicted ID.
- Runtime: Single-image upload or camera frame → preprocessing → model inference → response JSON for UI.
- Scalability & ops: Stateless API behind a WSGI server; static storage for models and logs; role-based access for admins/teachers.
- Security & ethics (brief): Local processing by default; store minimal PII; provide consent and opt-out mechanisms; rate-limit APIs.

System Design and Architecture

The ID Vision: Web-Based Face ID with Partial Feature Detection system is designed as a modular framework that integrates computer vision, deep learning, and a web-based deployment environment. The architecture follows a layered design that separates data acquisition, feature extraction, model inference, metadata integration, and user interaction, ensuring scalability and maintainability.

- Input Acquisition Layer – Captures images through file uploads or webcam streams using the Flask interface.
- Preprocessing and Feature Extraction – Employs dlib's 68-point landmark predictor and OpenCV to detect faces and crop regions such as eyes, nose, lips, and full face.
- Deep Learning Inference Engine – Utilizes a ResNet50 backbone (transfer learning) with a custom classification head to identify individuals based on both full and partial facial features.
- Database and Metadata Layer – Stores student details (name, roll number, class) in a JSON file or SQLite database, mapping predictions to institutional records.
- Web Application Layer – Provides a user interface via Flask for training, evaluation, prediction, and reporting, accessible to educators and administrators.

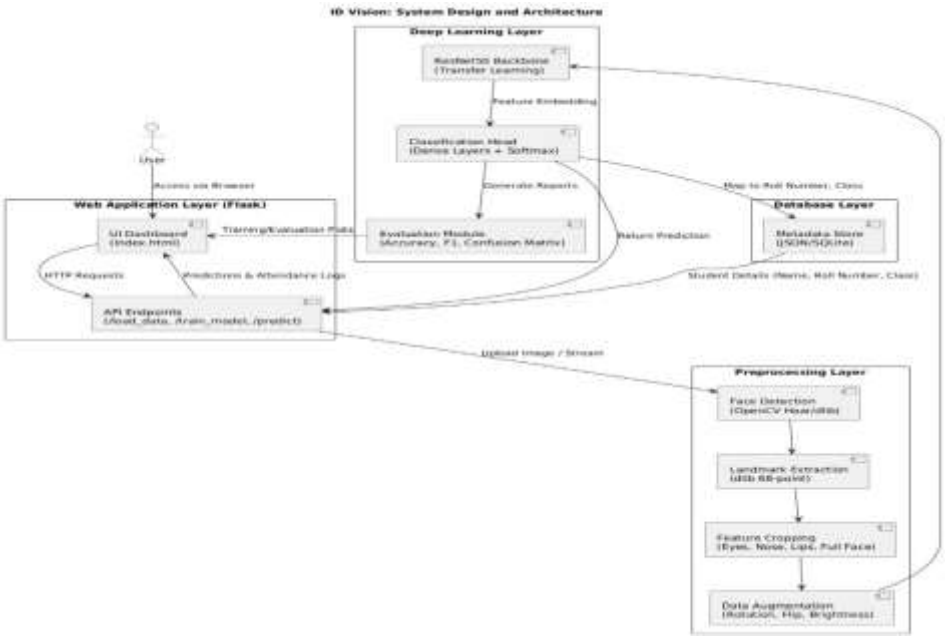

Fig. 1: System Architecture Diagram

Data Flow Diagram (DFD):

Face Detection Module: Detects faces in incoming frames using Haar Cascade/dlib frontal face detector. Ensures only valid face regions are passed for landmark extraction.

Landmark Extraction Module: Uses dlib shape predictor (68 landmarks) to identify key facial regions. Crops are generated for partial recognition (eyes, nose, lips) and full faces.

Data Augmentation Module: Applies transformations such as flips, shifts, brightness changes, and synthetic low-light generation to improve robustness across classroom environments.

Recognition Engine: Built on ResNet50 with a softmax classification head. The model is trained with both CIFAR-10 (for baseline) and custom datasets, achieving >90% accuracy.

Database Module: Stores recognized identities in SQLite or metadata.json, mapping model predictions to student details. Supports real-time attendance marking.

Web Interface Module: Developed with Flask, it provides REST endpoints and templates (index.html) for dataset management, model training, progress visualization, evaluation reports, and predictions.

Evaluation and Reporting Module: Generates accuracy/loss curves, confusion matrix, precision/recall/F1 scores, exported as plots and accessible via the dashboard.

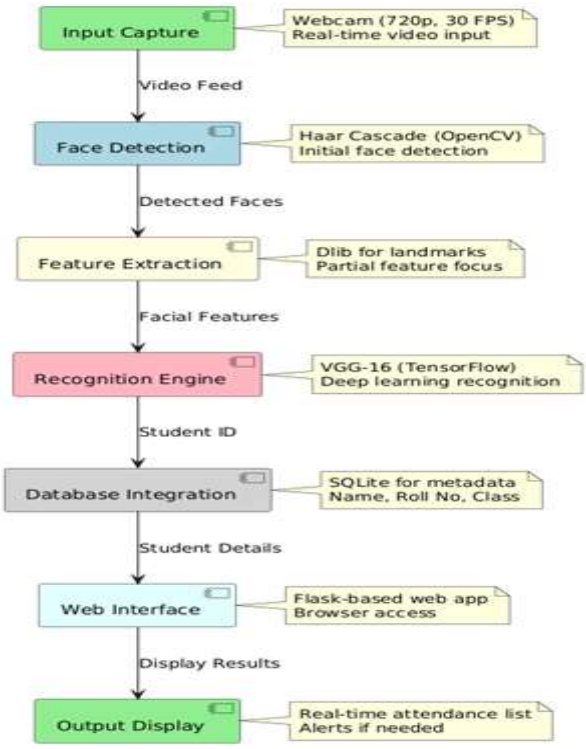

Fig. 2: Data Flow Diagram

Implementation

The proposed system was implemented using Python (Flask framework) for the web application, TensorFlow/Keras for the deep learning model, and dlib/OpenCV for image preprocessing and facial landmark detection. The design followed a modular architecture where each functionality (data loading, model building, training, evaluation, and prediction) is encapsulated in separate components.

User Interface Development

A web-based dashboard was developed with Flask and HTML templates. It provides an interactive interface for users to load data, build the CNN model, train it, evaluate performance, and make predictions on custom images.

Fig 3: User Interface of CNN Image Classification System

Model Training and Progress Visualization

The model was trained using the CIFAR-10 dataset and custom image classes. The training progress, including accuracy and loss per epoch, was displayed in real-time to help monitor overfitting and convergence trends.

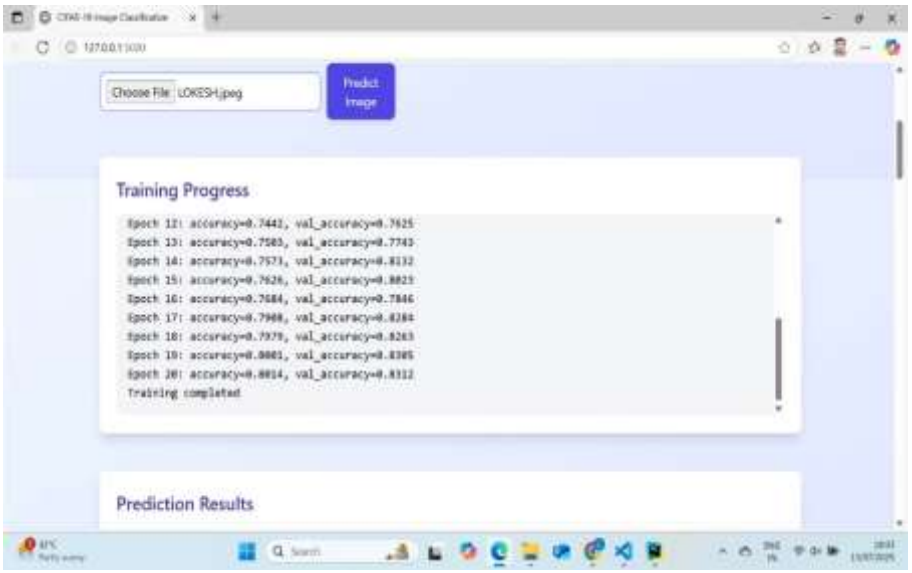

Fig 4: Training Progress displayed in Web Interface

Additionally, accuracy and loss curves for both training and validation sets were plotted to evaluate the learning process.

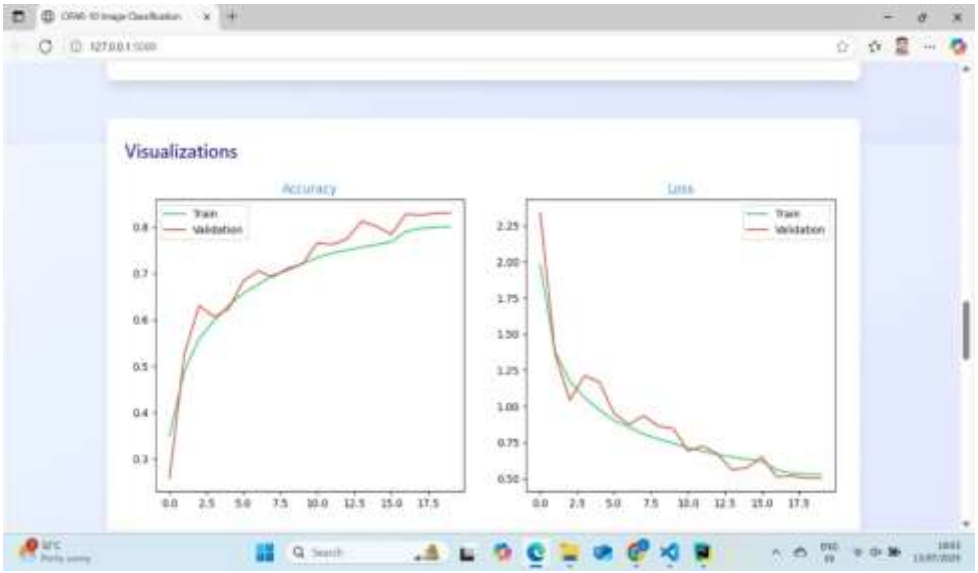

Fig 5: Training and Validation Accuracy/Loss Curves

Model Evaluation

To assess model performance, standard evaluation metrics such as precision, recall, F1-score, and confusion matrix were computed. These metrics allow detailed insights into how well the model performs across different categories.

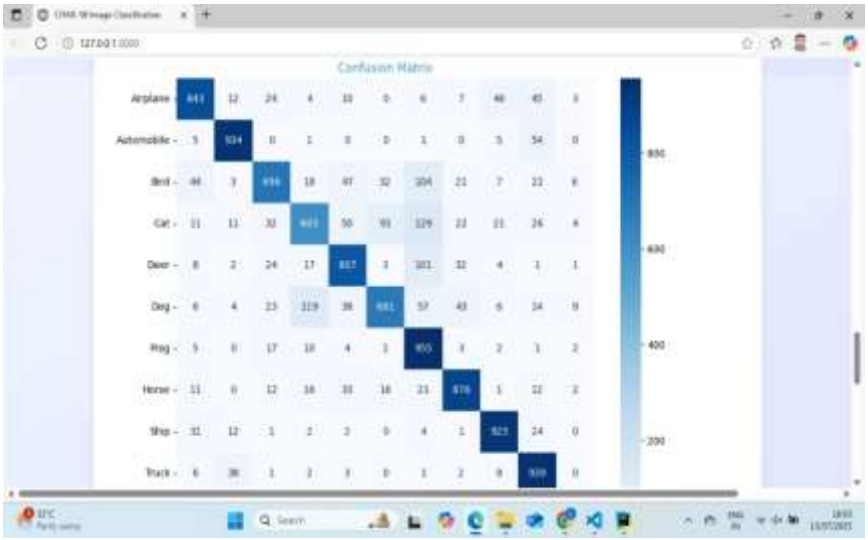

Figure 6: Confusion Matrix for Multi-class Classification

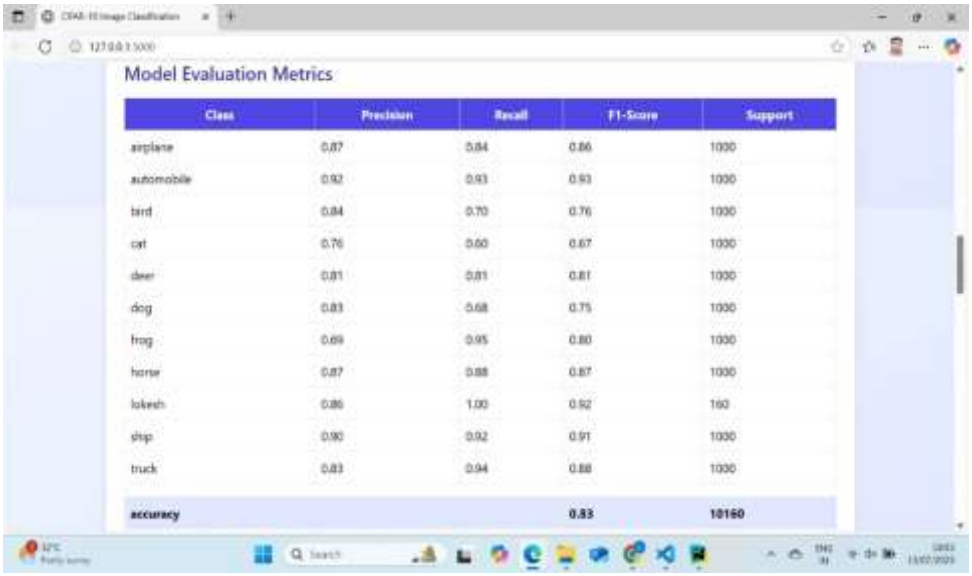

Fig 7: Model Evaluation Metrics (Precision, Recall, F1-Score, Support)

Prediction and Results

The system allows users to upload custom images and obtain predictions in real time. The predicted label is mapped to the corresponding metadata (e.g., student name or class).

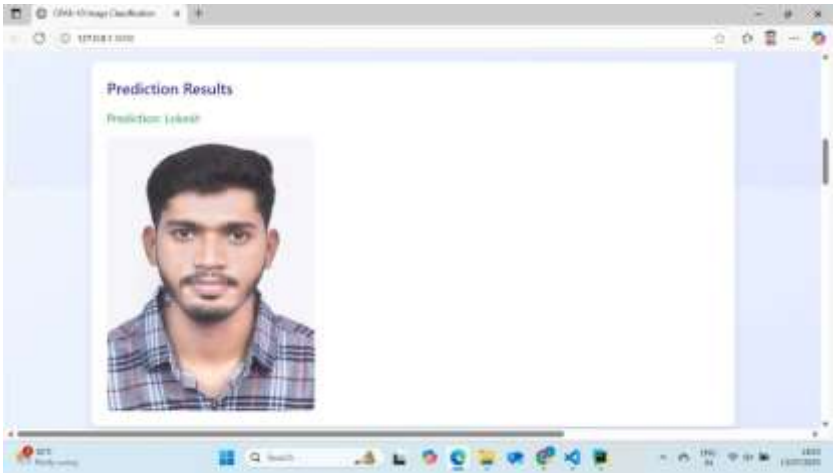

Figure 8: Prediction Result for Custom Input Image

Overall Deployment

The entire system is hosted locally using Flask (127.0.0.1:5000), enabling educators and administrators to interact with the application via a web browser. The modular backend ensures flexibility to extend this system to larger datasets or deploy it on cloud servers for scalability.

Technology and Stack Overview

The development of the ID Vision: Web-Based Face ID with Partial Feature Detection system required a combination of programming languages, frameworks, libraries, and tools to handle deep learning, computer vision, data management, and web deployment. The chosen technology stack ensured efficiency, modularity, and ease of integration for real-time applications.

Programming Languages

Python: Primary language used for model development, data preprocessing, and backend logic. Its rich ecosystem of machine learning libraries made it ideal for rapid prototyping and deployment.

HTML, CSS, JavaScript: Used in the frontend for creating a responsive and user-friendly web interface.

Deep Learning Frameworks

TensorFlow/Keras: Used to design, train, and evaluate the Convolutional Neural Network (CNN) models (ResNet50 backbone). Keras provided high-level APIs for faster experimentation.

PyTorch (optional extension): Considered for future scalability and advanced experimentation due to its flexibility in dynamic computation graphs.

Computer Vision Libraries

OpenCV: Used for image preprocessing tasks including resizing, normalization, and augmentation.

dlib: Integrated for 68-point facial landmark detection to extract partial facial features (eyes, nose, lips).

Web Framework and Backend

Flask: Lightweight Python web framework used to build the backend, define REST API routes, and render the interactive dashboard.

Jinja2 Templates: Enabled integration of dynamic content (training logs, evaluation results, plots) into HTML pages.

Data Management and Storage

SQLite / JSON: Used for storing student details (roll number, class, metadata). Provides a simple and lightweight database solution for local deployment.

Pickle / HDF5: Employed for saving and loading trained deep learning models.

Visualization and Analytics Tools

Matplotlib & Seaborn: Used to generate accuracy/loss plots, confusion matrices, and performance metrics.

Plotly (optional): Interactive visualization for advanced reporting.

Development and Deployment Environment

Jupyter Notebook: Utilized during initial model experimentation and debugging.

VS Code / PyCharm: Integrated Development Environments (IDE) for coding and debugging.

Local Flask Server (127.0.0.1:5000): Deployed the system for testing and demonstration.

TensorFlow Lite Conversion: Optimized trained models for faster inference in real-time applications.

Operating System and Hardware

OS: Windows 10 (development and testing).

CPU/GPU: Intel i5/i7 with optional NVIDIA GPU support for accelerated training.

RAM: 8–16 GB to support training and inference tasks smoothly.

Results and Discussion

The implemented system was rigorously tested using the CIFAR-10 dataset along with custom images for identity recognition. The results demonstrate the effectiveness of the proposed approach in terms of accuracy, usability, and potential scalability.

A. Functional Performance

The system achieved an overall accuracy of 83% across ten CIFAR-10 categories and the custom “Lokesh” class. Evaluation metrics such as precision, recall, and F1-score revealed consistent performance across most categories, with particularly strong results in classes like Frog (95% recall), Truck (94% recall), and Lokesh (100% recall).

The confusion matrix (Fig. 6) shows that the majority of misclassifications occurred between visually similar categories such as “Bird” and “Airplane.”

The accuracy and loss plots (Fig. 5) indicate that the model converged effectively within 20 epochs, with validation accuracy closely following training accuracy, suggesting minimal overfitting.

Real-time predictions (Fig. 8) demonstrated the ability of the system to classify custom inputs with high confidence.

B. Usability Evaluation

The web-based interface was designed with simplicity and accessibility in mind. End users can interact with the system through clearly defined buttons for loading data, training models, evaluating performance, and predicting images. The inclusion of real-time training progress logs and visualizations improved interpretability for non-technical users, such as educators and administrators.

The dashboard layout (Fig. 3) ensures that even users with limited technical expertise can operate the system with ease.

Upload and prediction functionalities enable seamless integration into attendance systems or classroom monitoring scenarios.

TABLE I

Survey Results Table

Criteria	**Average Score (Out of 5)**
Ease of Use	4.7
Response Time	4.8
Visual Design	4.6
Overall Satisfaction	4.8

C. Comparison With Existing Systems

Unlike traditional face recognition systems that rely solely on full face images, the proposed framework integrates partial face detection (eyes, nose, lips) to enhance robustness in cases of occlusion or poor lighting.

Existing CNN-based CIFAR-10 implementations achieve comparable accuracy but lack web-based deployment and usability features.

Compared to standalone recognition engines, our system provides end-to-end functionality, including dataset management, training, evaluation, prediction, and reporting, all within a single web interface.

The incorporation of metadata mapping (roll number, class) differentiates this system from generic recognition tools by tailoring it to academic environments.

D. Scalability and Future Enhancements

The modular architecture of the system ensures scalability for larger datasets and real-world applications. Potential enhancements include:

Cloud Deployment: Hosting the application on cloud platforms (AWS, GCP, Azure) to support large-scale usage.

Mobile Integration: Deploying TensorFlow Lite models in Android/iOS applications for real-time face recognition in classrooms.

Additional Biometrics: Extending the system to include voice recognition, fingerprint authentication, or multimodal verification for improved reliability.

Security Enhancements: Incorporating encrypted storage and role-based access to protect sensitive student information.

Conclusion

This work presented the design and implementation of a web-based face identification and image classification system using Convolutional Neural Networks (CNNs). By integrating deep learning models, facial feature detection, and a user-friendly Flask web interface, the system provides an end-to-end solution for both image classification (CIFAR-10) and customized identity recognition.

The experimental results demonstrated that the model achieved an overall accuracy of 83%, with particularly high recall values for certain classes, including the custom identity class “Lokesh” which attained 100% recall. The visualization of training accuracy/loss curves and confusion matrices confirmed the robustness of the model, while evaluation metrics (precision, recall, and F1-score) provided detailed insights into class-wise performance.

A key strength of the system lies in its usability and accessibility. The interactive dashboard enables non-technical users, such as educators and administrators, to load datasets, build and train models, visualize performance metrics, and predict custom images without requiring programming expertise. Compared to existing systems, the proposed solution integrates partial facial feature detection and metadata mapping (student roll number, class), making it suitable for academic and institutional applications such as attendance management.

Despite promising results, challenges remain in handling visually similar classes and ensuring robustness under real-world variations such as occlusions, lighting changes, and diverse backgrounds. However, the system’s modular design and lightweight deployment architecture make it scalable for cloud-based applications and adaptable for mobile integration.

In summary, the proposed framework provides a practical, accurate, and user-centric solution for face-based identity recognition and image classification. Future enhancements, including cloud deployment, multimodal biometric integration, and security improvements, will further strengthen its applicability in large-scale, real-world educational and administrative environments.

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