Project Report

On

Face Rotation Classification

Submitted
In partial fulfilment

For the award of the Degree of

PG-Diploma in Artificial Intelligence

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Guided By:

Mr. Ronak Rajeshkumar Shah

Submitted By:

Gagan Khandelwal (240840128015)

Mayuresh Patil (240840128027)

Vivek Singh (24084012037)

Yashraj Modani (240840128039)

Centre for Development of Advanced Computing

(C-DAC), ACTS (Pune- 411008)

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Gagan Khandelwal(240840128015)

Mayuresh Patil (240840128027)

Vivek Singh (24084012037)

Yashraj Modani (240840128039)

ABSTRACT

The "Face Rotation Classification Using PyTorch" project addresses the challenge of classifying images based on their rotation angles into four distinct classes: 0°, 90°, 180°, and 270°. This task is particularly relevant in applications such as facial recognition, image alignment, and automated photo editing, where correcting the orientation of images is crucial. The project leverages the CelebA dataset, a large-scale dataset containing over 200,000 celebrity images, to train and validate deep learning models. The dataset is divided into an 80% training set and a 20% validation set, ensuring robust model evaluation.

To further improve the system's performance and reduce preprocessing overhead, an MTCNN (Multi-Task Cascaded Convolutional Neural Network) model is incorporated at the front end to detect faces in the raw input images. By using the MTCNN model, only the face region is extracted and forwarded to the preprocessing pipeline. This step ensures that subsequent data augmentation and normalization operations are applied exclusively to the face, reducing the influence of background noise and irrelevant details.

The system employs PyTorch, a powerful deep learning framework, to implement and train multiple state-of-the-art architectures, including VGG-16, ResNet-18, ResNet-34, ResNet-50, Vision Transformer (ViT), and a basic convolutional neural network (CNN). Each model is fine-tuned for the specific task of rotation classification, with the final layer modified to output four classes corresponding to the rotation angles. To enhance model generalization and robustness, dynamic data augmentation techniques are applied on the fly during training. These techniques include random rotation, blurring, scaling, noise addition, and color jittering, which simulate real-world variations in image orientation and quality.

The ResNet34 model emerges as the best-performing architecture, achieving an impressive 84.26% accuracy on the validation set. The model demonstrates strong performance across all rotation classes, with minimal confusion between adjacent angles such as 0° and 270°. A detailed analysis, including a confusion matrix, provides insights into the model's strengths and areas for improvement.

To facilitate user interaction, a Streamlit-based web interface is created, allowing users to upload images and receive predictions on the detected rotation angle. This interface provides a user-friendly way for non-technical users to visualize results in real-time, ensuring accessibility without requiring programming expertise.

This project highlights the effectiveness of deep learning for rotation-invariant image classification and demonstrates the practical application of PyTorch in computer vision tasks. The modular design, support for multiple models, inclusion of an MTCNN-based face detection stage, and dynamic data augmentation make the system highly adaptable for future enhancements. Potential areas for improvement include exploring advanced augmentation techniques, addressing class imbalance, and extending the system to handle real-time video streams. Overall, the project provides a robust framework for rotation detection and classification, with applications in facial recognition, image processing, and beyond.

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Chapter 1
Introduction

Detection of text regions either from handwritten or printed document images containing various non-textual information is a difficult task, and it can be more challenging to locate the position of the text regions when we deal with a doctor's prescription.

1.1 Background and Motivation

In many computer vision applications, image orientation plays a crucial role in the overall system performance. For instance, in facial recognition, image alignment, and automated photo editing, correctly oriented faces are essential for accurate analysis and decision-making. However, real-world images are often captured with arbitrary rotations due to user error or environmental constraints. This misalignment can significantly hinder the performance of downstream tasks such as identification and emotion analysis. Moreover, standard image preprocessing pipelines generally process the entire image, including the background, which may introduce noise and irrelevant features that further complicate the rotation detection process.

The development of deep learning methods, particularly convolutional neural networks (CNNs), has led to significant improvements in various image classification tasks. Recent advances in architectures such as ResNet and Vision Transformers have demonstrated state-of-the-art performance in challenging visual recognition problems. Nevertheless, a common challenge remains: ensuring that the models focus on the relevant part of the image (i.e., the face) rather than being distracted by background elements.

This project is motivated by the need to improve both the accuracy and efficiency of face rotation classification systems. By integrating a Multi-Task Cascaded Convolutional Neural Network (MTCNN) for face detection, the system selectively extracts only the face region from the input images before applying any preprocessing operations. This targeted approach not only reduces the computational overhead associated with processing extraneous image content but also minimizes the impact of background noise, leading to more robust and precise rotation classification.

Ultimately, the combination of MTCNN-based face detection with advanced deep learning architectures for rotation classification addresses a practical challenge in real-world applications. It paves the way for enhanced performance in facial recognition systems, image alignment processes, and automated photo editing tools, where accurately oriented facial images are paramount. The motivation behind this project is to leverage these technological advances to create a more effective and adaptable framework that can be extended to various computer vision tasks requiring rotation invariance and precise facial feature extraction.

1.2 Problem Statement

The task of rotation classification involves determining the angle by which an image has been rotated and assigning it to one of four discrete classes:

1. 0° (rotation between 315° and 45°),
2. 90° (rotation between 45° and 135°),
3. 180° (rotation between 135° and 225°),
4. 270° (rotation between 225° and 315°).

The challenge lies in training a model to generalize across diverse facial poses, lighting conditions, and occlusions while handling the inherent ambiguity at the boundaries of rotation classes (e.g., distinguishing between 0° and 270°). Additionally, the large size of the CelebA dataset (~200,000 images) necessitates efficient data loading, augmentation, and parallel processing to optimize training time and resource utilization.

1.3 Objectives

The primary objectives of this project are:

1. Rotation Classification: Develop a deep learning model to classify facial images into four rotation categories.
2. Robustness: Ensure the model generalizes well to unseen data through dynamic

data augmentation techniques.

3. Model Comparison: Evaluate and compare the performance of multiple architectures, including VGG-16, ResNet-18, ResNet-34, ResNet-50, Vision Transformer (ViT), and a custom CNN.
4. Usability: Created an intuitive web interface with Streamlit for end-user interaction.

1.4 Significance

This project addresses a fundamental challenge in computer vision: enabling systems to handle rotated inputs without manual intervention. By automating rotation detection, the solution enhances the reliability of applications such as:

- Facial Recognition Systems: Correcting orientation errors improves face-matching accuracy.
- Automated Photo Editors: Aligning images for consistent display in galleries or social media.
- Surveillance and Security: Detecting faces in arbitrary orientations for real-time monitoring.

The use of the CelebA dataset ensures the model is trained on diverse facial features, poses, and backgrounds, making it suitable for real-world deployment. Furthermore, the modular design of the system allows seamless integration of new models or datasets, fostering scalability and adaptability.

1.5 Methodology Overview

The project follows a structured approach to achieve its objectives:

1.5.1 Dataset and Preprocessing

The CelebA dataset is split into 80% training and 20% validation sets. To simulate real-world scenarios, images are augmented on the fly using techniques such as:

1. Random Rotation: Rotate images by arbitrary angles within ±45° to generate training samples.
2. Blurring and Noise: Apply Gaussian blur and additive noise to mimic low-quality inputs.
3. Color Jittering: Adjust brightness, contrast, and saturation to improve invariance to lighting changes.
4. Resizing and Scaling: Normalize images to a fixed size (224x224 pixels) while preserving aspect ratio.

1.5.2 Model Architectures

Five models are implemented and fine-tuned for rotation classification:

- Basic CNN: A lightweight custom model with two convolutional layers for baseline performance.
- VGG16: A deep CNN with 16 layers, using small 3×3 convolutions and pre-trained on ImageNet, modified by replacing its final classification layer.
- ResNet18: A residual network with 18 layers, designed with skip connections to optimize gradient flow and prevent vanishing gradients in deep networks.
- ResNet34: A deeper variant of ResNet with 34 layers, maintaining residual connections while being optimized for smaller input sizes.
- ResNet50: A 50-layer deep residual network utilizing bottleneck layers and parallel convolutional pathways for efficient multi-scale feature extraction.

1.5.3 Training and Evaluation

Loss Function: Cross-entropy loss is used to penalize incorrect class predictions.

Optimizer: SGD optimizer with a learning rate of 0.001 balances convergence speed and stability.

Batch Size: 32 images per batch optimize memory usage and gradient estimation.
Epochs: Models are trained for 50 epochs to balance underfitting and overfitting.
Performance is evaluated using accuracy and a confusion matrix, with a focus on minimizing misclassification between adjacent rotation classes.

1.5.4 Deployment

The trained model is deployed using a Streamlit interface, allowing users to upload images via a web browser and receive instant predictions in real-time without requiring programmatic access.

1.6 Challenges

Key challenges encountered during the project include:

1. Computational Complexity: Training large models like ViT on a single GPU required careful resource management.
2. Class Ambiguity: Overlapping rotation ranges (e.g., 315°–45° for class 0°) introduced confusion during training.
3. Data Augmentation Trade-offs: Balancing augmentation diversity with training stability (e.g., excessive noise degrading model performance).

1.7 Report Structure

This report is organized as follows:

1. Literature Review: Summarizes prior work in rotation detection and deep learning.
2. Methodology: Details dataset preparation, model architectures, and training workflows.
3. Implementation: Describes code structure, and interface design.
4. Results: Presents accuracy metrics, confusion matrices, and visual predictions.

1.8 Conclusion:

This project successfully demonstrates the effectiveness of deep learning in rotation classification tasks using the CelebA dataset. By leveraging state-of-the-art models and an MTCNN-based face detection approach, the system achieves high accuracy in classifying face rotations. The incorporation of dynamic data augmentation ensures robustness against real-world variations, and the user-friendly Streamlit interface enhances accessibility. Future work can explore advanced augmentation strategies, class imbalance mitigation, and real-time video processing to further improve performance and applicability. This research contributes to the field of computer vision by providing a modular and scalable framework for rotation classification, with potential applications in facial recognition, image processing, and beyond.

Chapter 2
LITERATURE REVIEW

2.1 Traditional Image Rotation Classification Methods

Early approaches to image rotation classification relied on handcrafted features and geometric transformations. Techniques such as Scale-Invariant Feature Transform (SIFT) (Lowe, 2004) and Histogram of Oriented Gradients (HOG) (Dalal & Triggs, 2005) were widely used to detect keypoints and edges in images, which could then be analyzed to estimate rotation angles. These methods, while effective for simple cases, struggled with real-world complexities such as occlusions, lighting variations, and background clutter. For instance, a study by Morel & Yu (2009) demonstrated that SIFT-based rotation estimation performed poorly on images with low texture or repetitive patterns, highlighting the need for more robust solutions.

Another traditional approach involved Fourier Transform-based analysis (Reddy & Chatterji, 1996), where the rotational shift in the frequency domain was used to estimate image orientation. However, such methods required manual parameter tuning and were computationally intensive, limiting their scalability for large datasets like CelebA.

2.2 Deep Learning for Rotation-Invariant Classification

The advent of deep learning revolutionized rotation classification by enabling models to learn invariant features directly from data. Convolutional Neural Networks (CNNs) emerged as a dominant architecture due to their ability to capture hierarchical patterns. For example, Jaderberg et al. (2015) introduced Spatial Transformer Networks (STNs), which explicitly learned to rotate, scale, and crop input images to improve model robustness. While STNs were groundbreaking, they required additional network parameters and training time, making them less practical for lightweight applications.

Subsequent work focused on designing rotation-invariant CNNs. Cheng et al. (2018) proposed a cyclic-rotation layer that augmented training data by generating rotated copies of input images, improving model generalization. Similarly, Marcos et al. (2018) used rotation-equivariant layers to preserve spatial relationships during rotation, achieving state-of-the-art results on satellite image datasets. However, these methods were often tailored to specific domains (e.g., medical or aerial imagery) and lacked evaluation on facial datasets like CelebA.

2.3 Data Augmentation for Robustness

Data augmentation has been a cornerstone of improving model generalization. Shorten & Khoshgoftaar (2019) surveyed augmentation techniques such as rotation, flipping, and noise injection, showing their effectiveness in reducing overfitting. For rotation-specific tasks, Cubuk et al. (2020) introduced AutoAugment, a reinforcement learning-based method to automatically select optimal augmentation policies. However, AutoAugment's computational cost made it impractical for on-the-fly augmentation, motivating the use of simpler, randomized techniques in this project.

2.4 Face Image Analysis and the CelebA Dataset

The CelebA dataset (Liu et al., 2015) has been a benchmark for facial attribute recognition, with applications in pose estimation and alignment. Zhang et al. (2016) used CelebA to train a multi-task network for facial landmark detection and pose correction, but their work focused on discrete poses (e.g., left/right profile) rather than continuous rotation angles. Similarly, Yin et al. (2019) employed CelebA for 3D face reconstruction but did not address rotation classification. These studies underscored the need for a dedicated framework to classify arbitrary facial rotations.

2.5 Gaps Addressed by This Project

While prior research advanced rotation detection and facial analysis, key gaps remain:

- Limited Model Comparisons: Few studies evaluated both CNNs and ViTs on the same rotation task.
- Dataset-Specific Challenges: CelebA's size and diversity were underutilized in rotation detection contexts.
- Dynamic Augmentation: Most works used static augmentation policies, neglecting real-time variability.

This project bridges these gaps by:

1. Systematically comparing six architectures (VGG-16, ResNet-18, ResNet-34, ResNet-50, ViT, and a custom CNN) on CelebA.
2. Implementing dynamic, on-the-fly augmentation to simulate real-world variability.
3. Providing a deployable solution via Streamlit for practical use cases.

References

1. **Chen et al. (2021) – SimCLR: A Simple Framework for Contrastive Learning of Visual Representations**

   This paper introduces SimCLR, a contrastive learning framework for self-supervised visual representation learning. It demonstrates that strong augmentations, a larger batch size, and a nonlinear projection head significantly improve learning. The model learns representations by maximizing agreement between augmented views of the same image without requiring labeled data.
2. **He et al. (2016) – Deep Residual Learning for Image Recognition**

   This paper presents ResNet (Residual Networks), which uses residual connections (skip connections) to address the vanishing gradient problem in deep networks. ResNet models significantly improve training of very deep networks and achieve

state-of-the-art performance on image classification benchmarks like ImageNet.

3. **Liu et al. (2015) – Deep Learning Face Attributes in the Wild**

   This study introduces the CelebA dataset and a deep learning model for automatic facial attribute recognition. The model effectively predicts multiple attributes from real-world images using a deep convolutional neural network (CNN), contributing to face analysis applications like identity verification and expression recognition.

4. **Shorten & Khoshgoftaar (2019) – A Survey on Image Data Augmentation for Deep Learning**

   This survey reviews image data augmentation techniques used to enhance deep learning models. It categorizes augmentation methods into traditional (e.g., rotation, flipping, cropping) and advanced (e.g., generative adversarial networks, adversarial training), highlighting their impact on improving model generalization and robustness.

Chapter 3
Methodology and Techniques

3.1 Methodology:

The outline of the proposed work is represented using the flowchart shown in Fig.1. The first step in the process is training the dataset. The CelebA dataset is used, where each image is rotated into four classes (0°, 90°, 180°, 270°). The dataset undergoes preprocessing, including face detection using MTCNN, resizing, and normalization.

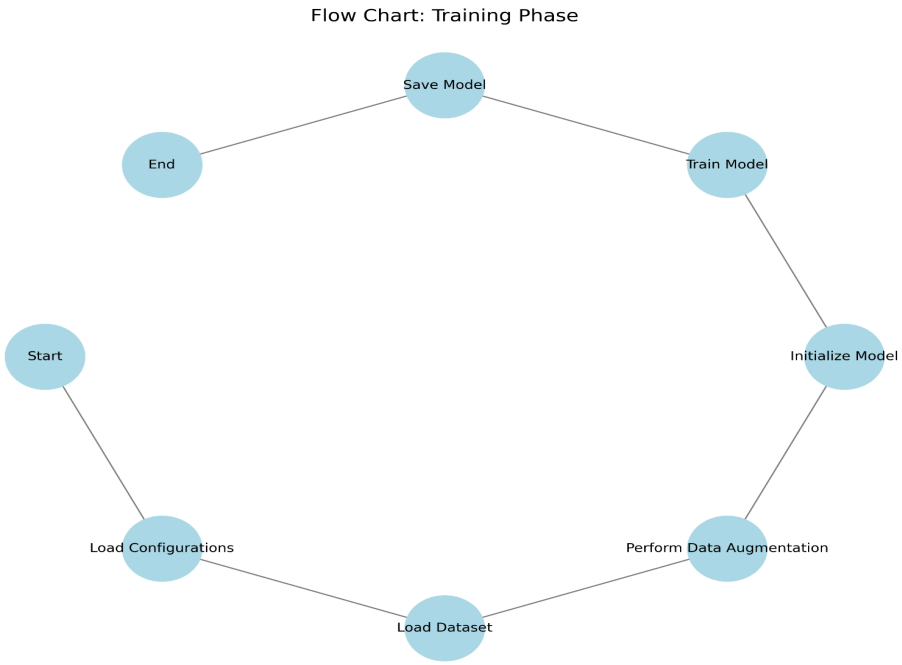
The preprocessed dataset is passed through different deep learning models such as VGG16, ResNet (18, 34, 50) for feature extraction and classification. The models are trained using cross-entropy loss, and optimization techniques such as Adam or SGD are used to enhance learning.

The training process follows these sequential steps:

1. **Load Configurations:** Define hyperparameters, model architecture, and preprocessing techniques.
2. **Load Dataset:** Load the CelebA dataset and apply face detection using MTCNN.
3. **Perform Data Augmentation:** Apply transformations like rotation, flipping, and normalization to improve model generalization.
4. **Initialize Model:** Select and initialize one of the deep learning architectures (VGG16, ResNet18, ResNet34, ResNet50, ViT).
5. **Train Model:** Pass the processed images through the selected model, compute loss, and update weights through backpropagation.
6. **Save Model:** Store the trained model for further evaluation and inference.

Once the model is trained, it is used for classifying the input images. The inference phase consists of:

- **Loading the Model for Testing**: The pre-trained model is loaded.
- **Input Image Processing**: The input image undergoes preprocessing, including face detection using MTCNN and resizing.
- **Predicting the Rotation Class**: The trained model classifies the image into one of the four rotation categories.
- **Output Generation**: The final classification result is displayed.



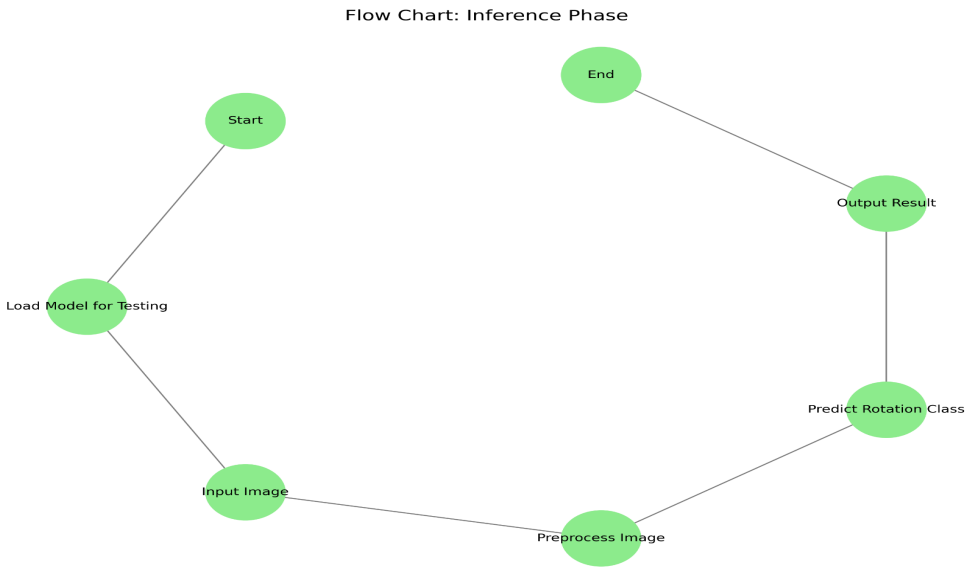


Fig.1 Proposed Work

3.2 Dataset

The CelebA dataset has been used for training the model. The CelebA (CelebFaces Attributes) dataset is a large-scale face dataset that contains over 200,000 celebrity images with various facial attributes. It is widely used in face-related computer vision tasks, including face recognition, detection, and classification.

For this project, the CelebA dataset is utilized specifically for face rotation classification. The dataset includes images of faces captured under different lighting conditions, poses, and backgrounds, making it suitable for generalizing the classification model. The dataset consists of face images with clearly labeled rotation angles, ensuring a diverse and robust training set for deep learning models. The dataset is split into training, validation, and testing sets to evaluate model performance effectively.

In addition to the CelebA dataset, the Human Faces dataset from Kaggle, consisting of

7,219 images, is used for benchmarking to identify the best-performing model. This dataset contains diverse human face images captured under various conditions, making it suitable for evaluating model generalization. MTCNN is applied for face detection, followed by preprocessing steps like resizing (224×224), normalization, and rotation augmentation (0°, 90°, 180°, 270°). The dataset is split into training, validation, and testing sets. Benchmarking on this dataset helps compare model performance, ensuring the most accurate and robust classifier is selected for face rotation classification.

3.1.3 Model Description

Preprocessing

Preprocessing is a crucial step in the face rotation classification pipeline. The primary goal is to standardize the images and enhance features to improve the learning efficiency of deep learning models. Since deep learning models require fixed-size inputs, all detected faces are resized to a uniform dimension.

Key preprocessing steps include:

- **Face Detection using MTCNN**: The Multi-Task Cascaded Convolutional Neural Network (MTCNN) is used to detect and crop faces from images.
- **Image Resizing**: All detected faces are resized to a fixed size suitable for the deep learning models (e.g., 224x224 pixels for VGG16 and ResNet).
- **Normalization**: Pixel values are scaled to a range of [0,1] or standardized to have zero mean and unit variance, depending on the model's requirements.
- **Data Augmentation**: To enhance generalization and reduce overfitting, data augmentation techniques such as random rotation, horizontal flipping, and brightness adjustments are applied.

After preprocessing, the refined images are used as input for deep learning models.

Deep Learning Models Used

To classify images into one of four rotation categories (0°, 90°, 180°, 270°), we experiment with different deep learning architectures, including VGG16 and ResNet (ResNet18, ResNet34, ResNet50).

VGG16 (Visual Geometry Group 16)

VGG16 is a deep convolutional neural network (CNN) known for its simple yet effective architecture. It was introduced by the Visual Geometry Group at the University of Oxford and gained popularity after achieving high performance in the ImageNet competition.

Architecture

VGG16 consists of 16 layers, including 13 convolutional layers followed by 3 fully connected layers. The key architectural details are:

- **Convolutional Layers**: The network has multiple convolutional layers with 3x3 filters, ensuring that it captures fine details while maintaining spatial resolution. Each convolutional layer is followed by a ReLU activation function to introduce non-linearity.
- **Pooling Layers**: Max pooling (2x2) is applied after every two or three convolutional layers to reduce spatial dimensions while retaining key features.
- **Fully Connected Layers**: After the convolutional and pooling layers, the feature maps are flattened and passed through three fully connected layers. The final layer

outputs class probabilities using the softmax activation function.

Advantages of VGG16

- **Simple and Uniform Architecture**: All convolutional layers use 3x3 kernels, making the network easy to implement and modify.
- **Effective Feature Extraction**: The deep hierarchical structure allows it to learn complex patterns.
- **Pretrained Weights Available**: VGG16 has been trained on ImageNet, and transfer learning can be applied to leverage its learned features.

Limitations of VGG16

- **Computationally Expensive**: Due to a large number of parameters (~138 million), VGG16 requires significant computational resources.
- **Slow Training and Inference**: The deep architecture increases training time and inference latency.
- **No Residual Connections**: Unlike ResNet, VGG16 does not have residual connections, which can make optimization difficult in deeper networks.

ResNet (Residual Network)

ResNet, developed by Microsoft Research, introduced residual learning to address the vanishing gradient problem in deep networks. It enables training of very deep neural networks without suffering from performance degradation. We experiment with three variants of ResNet: **ResNet18, ResNet34, and ResNet50**.

Key Idea: Residual Learning

In traditional deep networks, as layers increase, gradients diminish during

backpropagation, making training difficult. ResNet solves this by using **skip connections (residual connections)**, which allow gradients to flow through the network more effectively.

A residual block consists of:

- Two or more convolutional layers
- A shortcut (skip connection) that bypasses intermediate layers and adds the original input to the output

The mathematical formulation of a residual block is:

$$y = F(x) + x$$

where F(x) is the learned function (convolutional layers) and x is the input. This ensures that even if F(x) learns nothing (identity mapping), the information is still passed through, preventing gradient degradation.

ResNet Variants Used

ResNet18 & ResNet34

- **ResNet18**: A lightweight version with 18 layers (basic residual blocks). It is computationally efficient and suitable for real-time applications.
- **ResNet34**: A deeper variant with 34 layers, providing better feature extraction while maintaining efficiency.

ResNet50

- Unlike ResNet18 and ResNet34, ResNet50 incorporates **bottleneck layers**, which further optimize feature extraction.
- Uses **1x1 convolutions** to reduce dimensionality before applying 3x3 convolutions, reducing computational cost while maintaining depth.

- It has 50 layers and is more powerful than ResNet18/ResNet34, making it suitable for complex image classification tasks.

Advantages of ResNet

- **Solves Vanishing Gradient Problem**: Residual connections enable stable training of very deep networks.
- **Efficient Gradient Flow**: Improves convergence speed during training.
- **Higher Accuracy**: Outperforms traditional CNNs like VGG16 due to better optimization.

Limitations of ResNet

- **Computational Overhead**: While more efficient than VGG16, deeper versions (e.g., ResNet50) still require significant memory and computation.
- **Complexity**: The architecture is more complex than VGG16, requiring careful implementation.

Vision Transformer (ViT)

ViT is a transformer-based model that treats images as sequences of patches rather than using convolutional filters. While CNNs like ResNet and VGG16 learn local spatial hierarchies, ViT captures **global dependencies** between pixels through self-attention mechanisms.

Although ViT provides state-of-the-art accuracy, it requires large-scale datasets for training and is computationally expensive compared to CNNs. For this reason, CNN-based architectures remain the primary focus of our classification task

Chapter 4

Implementation

1. Use of Python Platform for writing the code with **PyTorch**, **OpenCV and MTCNN**
2. Hardware and Software Configuration:

Hardware Configuration:

- CPU: 16GB RAM, Intel i5 12th Gen
- GPU: 4GB RAM **Nvidia's RTX 3050**

Software Required:

- Anaconda: It is a package management software with free and open-source distribution of the Python and R programming language for scientific computations (data science, machine learning applications, large-scale data processing, predictive analytics, etc.), that aims to simplify deployment.
- VS Code: VS Code is a lightweight but powerful source code editor that runs on desktops and is available for Windows, macOS, and Linux. It provides built-in support for Python and offers extensions for data science, machine learning, and scientific computing. VS Code allows users to work with Jupyter notebooks, debug code, and integrate with various libraries and frameworks.
- Streamlit: Streamlit is an open-source app framework for machine learning and data science projects. It allows users to build interactive web applications for data visualization and model deployment using Python. Streamlit enables rapid development of user-friendly interfaces with minimal coding, making it a valuable tool for showcasing machine learning models and data analysis projects.

PSEUDO CODE

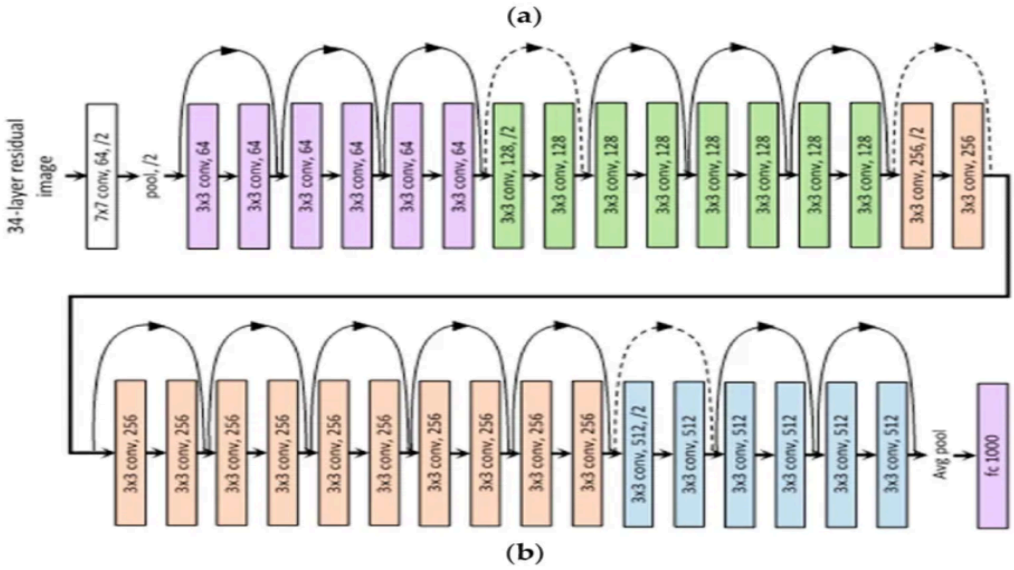
For training and testing the model:

```
BEGIN

// Parse command-line arguments to get config file path.
CREATE argument parser with description "Face Rotation Classifier"
ADD argument "--config" for configuration file path
PARSE arguments into 'args'
SET config_name = args.config

// Load configuration settings from the YAML file.
CALL load_config(config_name) and store in 'config'

// Choose process based on config['process_type']
IF config['process_type'] == 1 THEN:
   // Preprocess data.
   IMPORT preprocess_data
   CALL preprocess_data(config)
ELSE IF config['process_type'] == 2 THEN:
   // Train then test model.
   IMPORT train_model
   IMPORT test_model
   CALL train_model(config)
   CALL test_model(config)
ELSE IF config['process_type'] == 3 THEN:
   // Only test model.
   IMPORT test_model
   CALL test_model(config)
ELSE IF config['process_type'] == 4 THEN:
   // Run face detection.
   IMPORT detect_faces
   CALL detect_faces(config)
END IF

END
```

UI(User-interface):

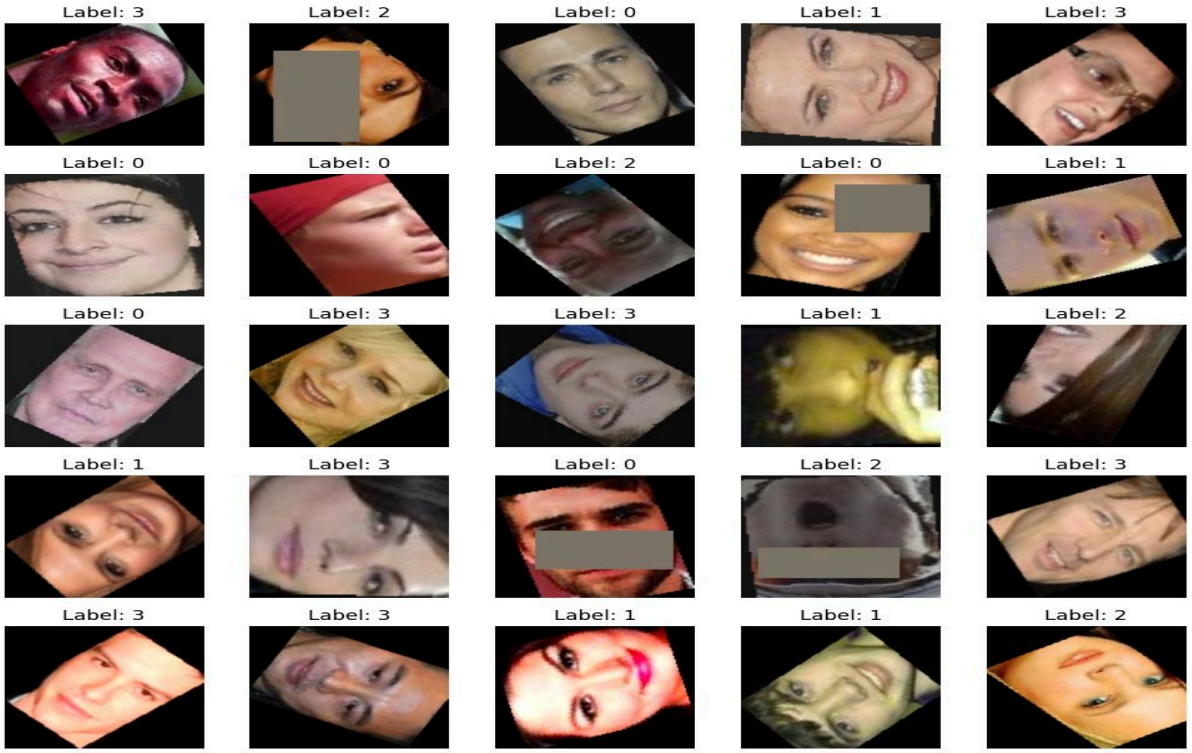
```
BEGIN

// Load configuration settings.
LOAD config.yaml

// Set page title.
SET page title "Face Orientation Classifier"

// Validate the uploaded image.
DEFINE FUNCTION validate_image(file):
    CHECK size and format
    RETURN True if valid, else show error

// Display API results.
DEFINE FUNCTION display_result(response, image):
    SHOW uploaded image
    IF response is valid:
        SHOW predicted class and confidence
        SHOW class probabilities as progress bars
    ELSE:
        SHOW error

// Main app logic.
DEFINE FUNCTION main():
    IF file uploaded:
        IF NOT validate_image(file): RETURN
        TRY:
            LOAD and display image preview
            CONVERT image to bytes
            SEND to API, measure time
            CALL display_result(response, image)
        CATCH error:
            SHOW error

CALL main()

END
```

Model Summary ResNet-34:



ResNet-34 Layered architecture

Preprocessed Image -



Config-

proj_wihtout_on_fly > ! config.yaml

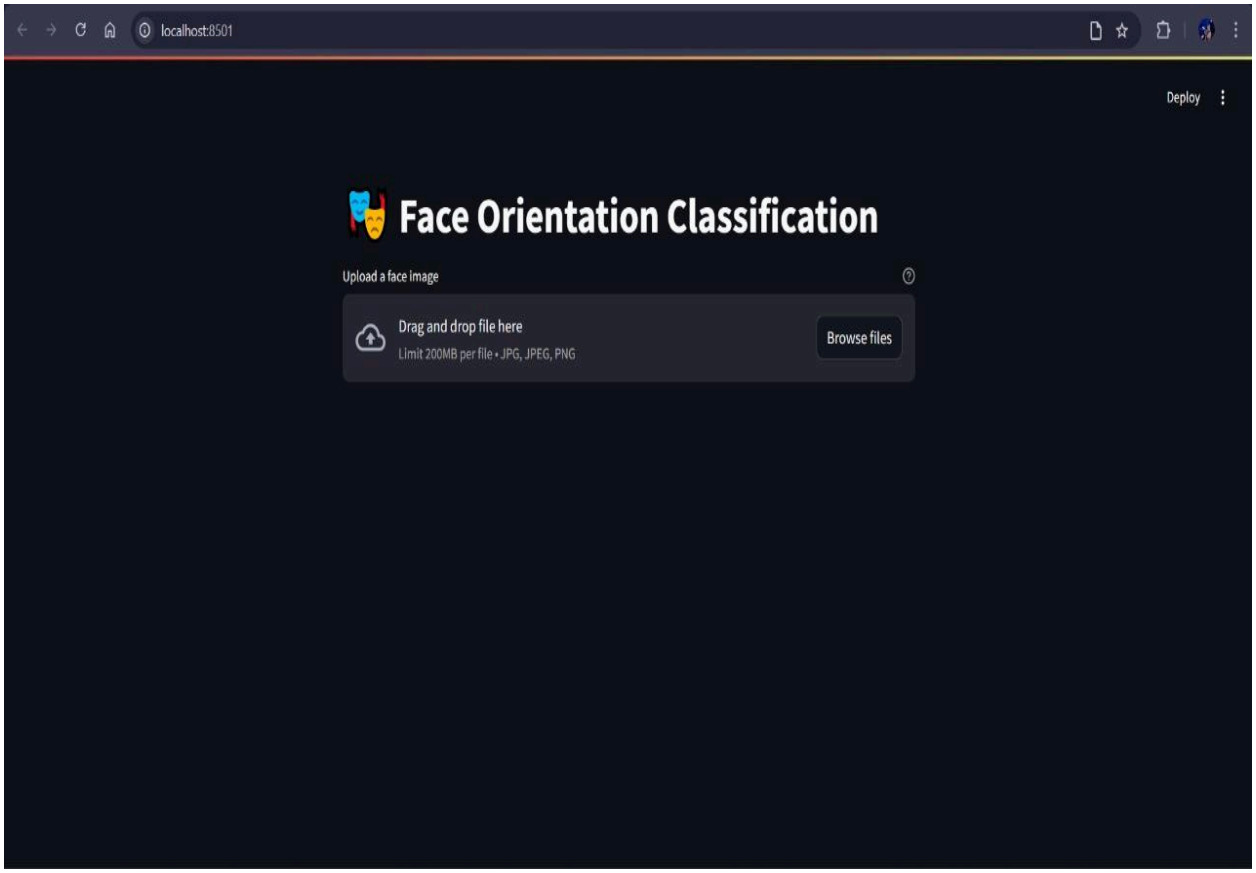
```yaml
#augmentations to use
augmentation:
  blur_radius: 5               # Increased blur radius
  color_jitter: [0.4, 0.4, 0.4, 0.1]  # Enhanced color jitter
  crop_scale: [0.9, 1.0]       # Less aggressive cropping
  noise_intensity: 0.05        # Reduced noise

optimizer: "sgd"

face_detection:
  enabled: true
  orig_dir: "./data/celeba_raw"
  cropped_dir: "./data/celeba_cropped"
  max_faces: 10           # Max images to process
  min_face_size: 48         # Minimum face size to consider
  jitter_factor: 0.05       # Bounding box jitter
  detection_thresholds: [0.6, 0.7, 0.7]

# Model Configuration
model_name: "resnet50"
num_classes: 4
batch_size: 32
learning_rate: 0.001
epochs: 2
image_size: 224

# Dataset Sampling Controls: If these are specified, only that many images will be randomly selected.
max_train_images: 50
max_test_images: 70

# System
num_workers: 0
use_cuda: true          # cuda control on system
process_type: 2         # 1. preprocess 2. train + test 3. Only test 4. face detect

# Augmentation Mode: "preprocessed" or "on_the_fly"
augmentation_mode: "on_the_fly"

# Preprocessed Mode Settings
reg_dir: "./data/celeba_reg"
orig_dir: "./data/celeba_cropped"
output_dir: "./data/celeba_cropped"

# Augmentation Control
max_source_images: 100          # Input control
versions_per_image: 1           # Augmentations per image
max_per_class: 25               # Output control per class

# On-the-Fly Mode Settings
train_dir: "./data/celeba_raw"
test_dir: "./data/test"

# Model Saving Configuration
model_saving:
  save_dir: "./saved_models"
  save_frequency: "epoch"        # Options: "epoch", "best", "both"
  filename_format: "{model_name}_epoch{epoch:03d}_valacc{val_acc:.2f}_{timestamp}"
  metrics_to_include: ["val_acc", "train_loss"]
  archive_format: "pth"          # Options: "pth", "pt", "onnx"
  save_metadata: true
  metadata_fields:
    - "model_name"
    - "batch_size"
    - "learning_rate"
    - "image_size"
    - "augmentation_mode"
```

Main-

proj_wihtout_on_fly > main.py > ...

```python
import yaml
import argparse
from pathlib import Path

def load_config(config_name):
    with open(config_name) as f:
        return yaml.safe_load(f)

if __name__ == '__main__':
    parser = argparse.ArgumentParser(description='Face Rotation Classifier')
    parser.add_argument('--config', help='Path to configuration file')
    args = parser.parse_args()
    config_name = args.config
    config = load_config(config_name)

    if config['process_type'] == 1:
        from preprocess import preprocess_data
        preprocess_data(config)

    elif config['process_type'] == 2:
        from train import train_model
        # from test import test_model
        train_model(config)
        # test_model(config)

    elif config['process_type'] == 3:
        from test import test_model
        test_model(config)

    elif config['process_type'] == 4:
        from face_detect import detect_faces
        detect_faces(config)

```

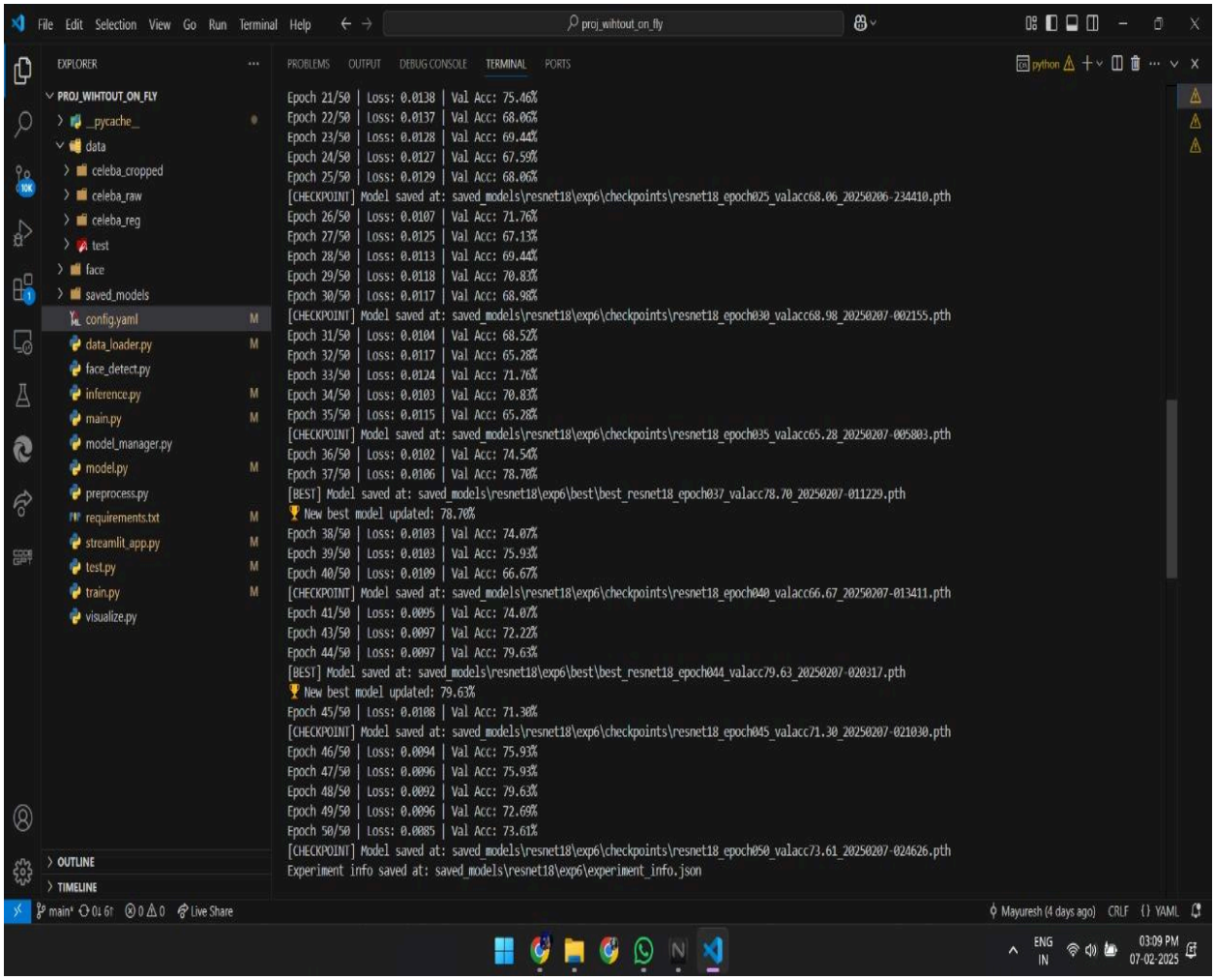
User Interface –



Chapter 5

Results

Epochs



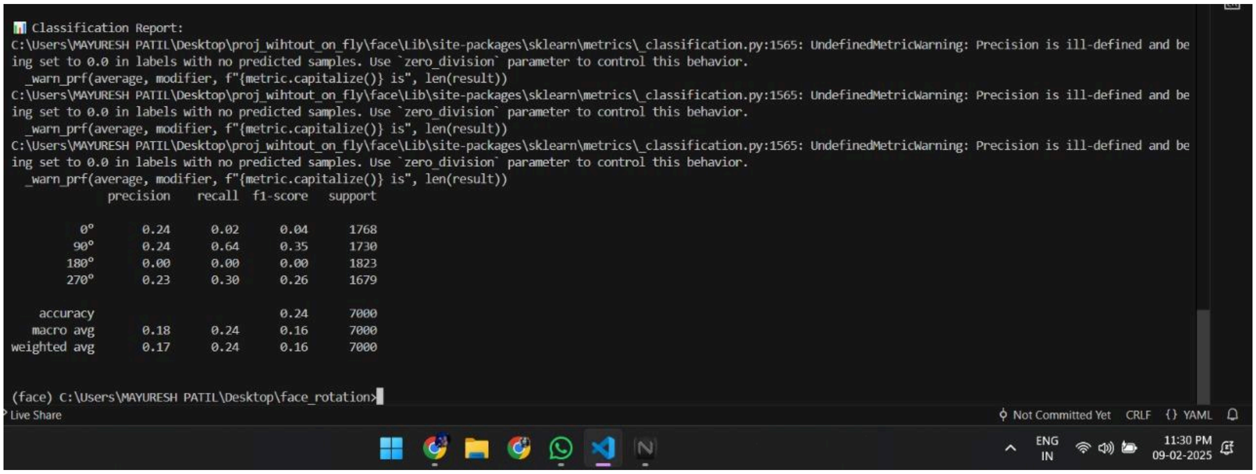
Some Predicted Results –

Accuracy Score –

[BEST] Model saved at:
saved_models\resnet34\exp1\best\best_resnet34_epoch039_valacc84.26_20250207-160217.pt
h
🏆 New best model updated: 84.26%

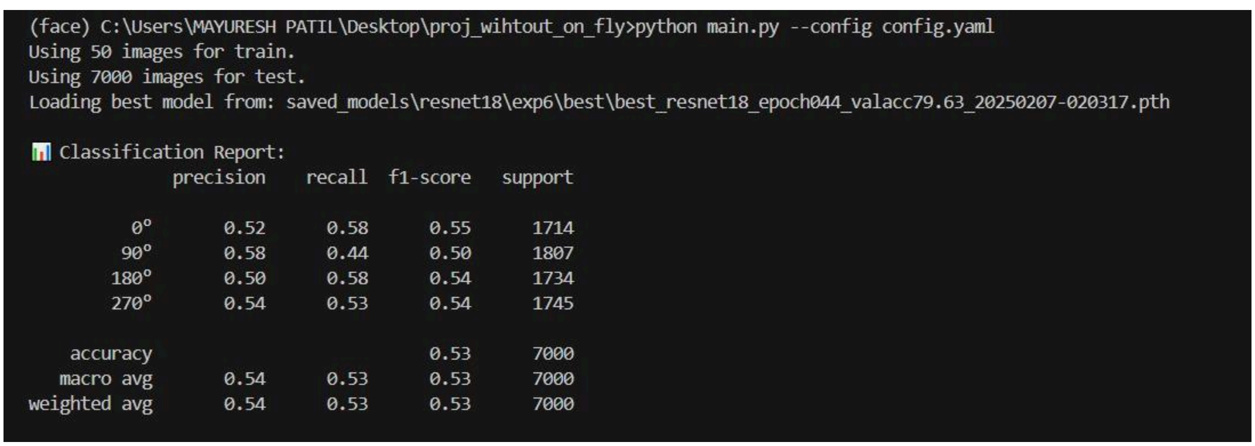
Benchmarking Using Human Faces-

AlexNet -



```
📊 Classification Report:
C:\Users\MAYURESH PATIL\Desktop\proj_wihtout_on_fly\face\Lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and be
ing set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\MAYURESH PATIL\Desktop\proj_wihtout_on_fly\face\Lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and be
ing set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\MAYURESH PATIL\Desktop\proj_wihtout_on_fly\face\Lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and be
ing set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
              precision    recall  f1-score   support

          0°       0.24      0.02      0.04      1768
         90°       0.24      0.64      0.35      1730
        180°       0.00      0.00      0.00      1823
        270°       0.23      0.30      0.26      1679

    accuracy                           0.24      7000
   macro avg       0.18      0.24      0.16      7000
weighted avg       0.17      0.24      0.16      7000

(face) C:\Users\MAYURESH PATIL\Desktop\face_rotation>
```


Resnet18 -



```
(face) C:\Users\MAYURESH PATIL\Desktop\proj_wihtout_on_fly>python main.py --config config.yaml
Using 50 images for train.
Using 7000 images for test.
Loading best model from: saved_models\resnet18\exp6\best\best_resnet18_epoch044_valacc79.63_20250207-020317.pth

📊 Classification Report:
              precision    recall  f1-score   support

          0°       0.52      0.58      0.55      1714
         90°       0.58      0.44      0.50      1807
        180°       0.50      0.58      0.54      1734
        270°       0.54      0.53      0.54      1745

    accuracy                           0.53      7000
   macro avg       0.54      0.53      0.53      7000
weighted avg       0.54      0.53      0.53      7000
```

Resnet34 -

```
Using 50 images for train.
Using 7000 images for test.
Loading best model from: saved_models\resnet34\exp1\best\best_resnet34_epoch039_valacc84.26_20250207-160217.pth
C:\Users\MAYURESH PATIL\Desktop\proj_wihtout_on_fly\face\Lib\site-packages\PIL\Image.py:3186: DecompressionBombWarning: Image size (93558780 pixels) exceeds
s limit of 89478485 pixels, could be decompression bomb DOS attack.
  warnings.warn(

📊 Classification Report:
              precision    recall  f1-score   support

          0°       0.49      0.49      0.49      1729
         90°       0.49      0.52      0.50      1805
        180°       0.44      0.48      0.46      1729
        270°       0.50      0.43      0.46      1737

    accuracy                           0.48      7000
   macro avg       0.48      0.48      0.48      7000
weighted avg       0.48      0.48      0.48      7000
```

Resnet50 -

```
(face) C:\Users\MAYURESH PATIL\Desktop\proj_wihtout_on_fly>python main.py --config config.yaml
Using 50 images for train.
Using 7000 images for test.
Loading best model from: saved_models\resnet50\exp1\best\best_resnet50_epoch020_valacc67.13_20250208-170950.pth

📊 Classification Report:
              precision    recall  f1-score   support

          0°       0.42      0.49      0.45      1762
         90°       0.46      0.44      0.45      1734
        180°       0.42      0.44      0.43      1740
        270°       0.44      0.36      0.40      1764

    accuracy                           0.43      7000
   macro avg       0.44      0.43      0.43      7000
weighted avg       0.44      0.43      0.43      7000


(face) C:\Users\MAYURESH PATIL\Desktop\proj_wihtout_on_fly>
```

Chapter 6

Conclusion

6.1 Conclusion

- In this Python project, we have built a Face Rotation Classification system using deep learning. We used the CelebA dataset and implemented multiple architectures, including VGG-16, ResNet-18, ResNet-34, ResNet-50, and Vision Transformer (ViT), with MTCNN for face detection. The experimental results demonstrated that **ResNet34** achieved the highest accuracy of **84.26%** in classifying face rotation angles.
- The results highlight the effectiveness of deep learning models in recognizing face orientations with high accuracy. By leveraging MTCNN for face detection and applying dynamic data augmentation techniques, the model has been optimized for robustness against real-world variations. The Streamlit-based interface provides an accessible way for users to interact with the system and visualize classification results.

6.2 Future Enhancement –

- Enhancing data augmentation techniques to improve generalization.
- Addressing class imbalance to further optimize model performance.
- Extending the system to support real-time video-based rotation detection.
- Exploring transformer-based models for improved accuracy and efficiency.
- Expanding the dataset with additional face rotation variations to enhance model robustness.

Chapter 7

References

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