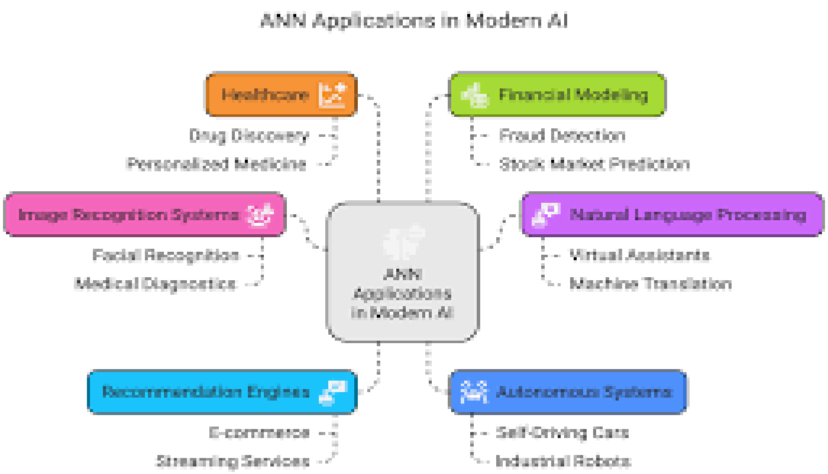
Module 1: GROUP TASK

Modeling ANN in Real Life: Group selects an application (e.g., facial recognition or noise cancellation), map ANN structure, neuron types, and suitable learning law

Introduction

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of the human brain. They consist of interconnected artificial neurons that process information and learn patterns from data. Modern ANN research was significantly advanced by scientists such as Geoffrey Hinton, who contributed to the development of deep learning architectures.



In real life, ANNs are used in:

- Facial recognition
- Speech recognition
- Noise cancellation
- Medical diagnosis
- Fraud detection
- Autonomous vehicles

In this report, we select **Facial Recognition** as the application and model how an ANN system works in real-world scenarios. The report covers:

- Real-world problem description
- ANN architecture mapping
- Neuron types
- Learning laws
- Training process
- Evaluation
- Advantages and challenges

Real-Life Application: Facial Recognition

Facial recognition is the process of identifying or verifying a person using their facial features.

Real-Life Examples

- Smartphone face unlock
- Airport security systems
- Attendance systems
- Social media photo tagging
- Law enforcement surveillance

A popular example is Apple Inc.'s Face ID system, which uses deep neural networks to recognize faces securely.

Problem Definition

Given:

- Input: An image of a face
- Output: Identity of the person

Type of Problem:

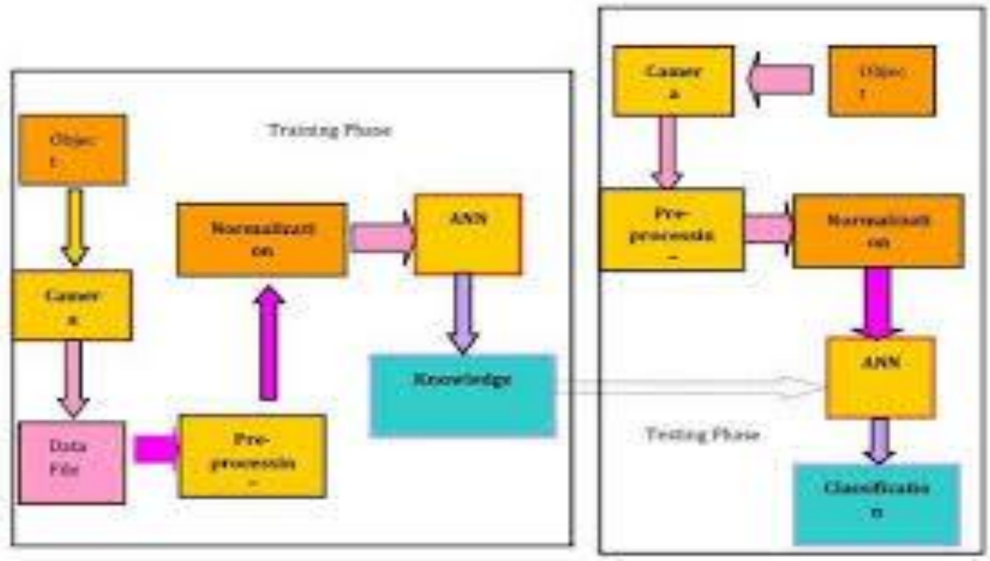
- Multi-class classification
- Supervised learning

Objective:

Build an ANN model that learns facial features and classifies them correctly.

ANN Structure for Facial Recognition

Facial recognition uses **Deep Neural Networks (DNNs)**, specifically **Convolutional Neural Networks (CNNs)**.



4.1 Layers in ANN Architecture

1. Input Layer
2. Convolutional Layers
3. Activation Layers
4. Pooling Layers
5. Fully Connected Layers
6. Output Layer

Mapping ANN Structure

5.1 Input Layer

- Accepts image pixels (e.g., 128×128×3 RGB image)
- Each pixel acts as an input neuron

If image size = 128×128×3
Total input neurons = 49,152

5.2 Hidden Layers

(A) Convolutional Layer

Purpose:

- Extract features (edges, textures, shapes)

Each neuron processes a small region of the image.

(B) Activation Layer

Common Activation Functions:

- ReLU (Rectified Linear Unit)
- Sigmoid
- Tanh

ReLU formula:

$$f(x) = \max(0, x)$$

ReLU helps avoid vanishing gradient problems.

(C) Pooling Layer

Purpose:

- Reduce dimensionality
- Keep important features

Common type: Max Pooling

5.3 Fully Connected Layer

- Combines extracted features
- Performs classification

5.4 Output Layer

Uses **Softmax function** for multi-class classification:

$$P(y_i) = \frac{e^{z_i}}{\sum e^{z_j}}$$

Output:

- Probability distribution of identities

Types of Neurons Used

Layer	Neuron Type	Function
Input	Passive neurons	Receive pixel values
Convolution	Feature detector neurons	Detect patterns
Hidden	ReLU neurons	Introduce non-linearity
Output	Softmax neurons	Classification

Learning Law for Facial Recognition

For deep neural networks, the suitable learning law is:

7.1 Supervised Learning

- Data labeled with person names
- Model compares predicted output with actual label

7.2 Backpropagation Algorithm

Developed and popularized by researchers including Geoffrey Hinton.

Backpropagation steps:

1. Forward propagation
2. Compute loss
3. Calculate gradients
4. Update weights

Weight update rule:

$$w = w - \eta \frac{\partial L}{\partial w}$$

Where:

- η= learning rate
- L= loss function

Loss Function

For facial recognition:

Cross-Entropy Loss

$$L = -\sum y \log(\hat{y})$$

Used because:

- Works well with Softmax
- Suitable for classification

Training Process

Step 1: Data Collection

- Collect thousands of labeled face images

Step 2: Preprocessing

- Resize images
- Normalize pixel values
- Data augmentation

Step 3: Training

- Feed images into ANN
- Compute loss
- Apply backpropagation
- Update weights

Step 4: Validation

- Check accuracy on test data

Performance Metrics

Metric	Description
Accuracy	Correct predictions / Total
Precision	Correct positive predictions
Recall	Detection rate
F1 Score	Balance of precision and recall

Real-World Architecture Example

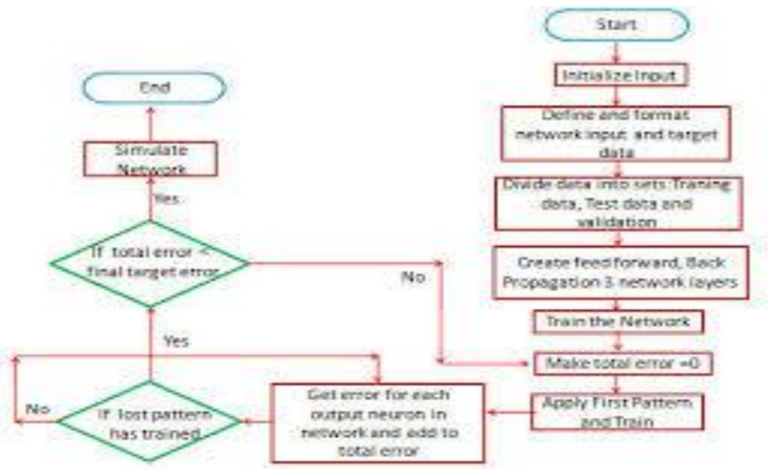
Popular CNN models used:

- Google's FaceNet
- Facebook DeepFace
- VGGNet
- ResNet

These models use deep architectures with millions of parameters.

ANN Flow Diagram (Conceptual)

Input Image → Convolution → ReLU → Pooling → Fully Connected → Softmax → Identity Output



Advantages of ANN in Facial Recognition

1. High accuracy
2. Automatic feature extraction
3. Learns complex patterns
4. Scalable for large datasets

Challenges

1. Requires large datasets
2. High computational power
3. Privacy concerns
4. Bias in training data

Ethical Considerations

- Data privacy
- Surveillance misuse
- Bias against minority groups
- Data security

Organizations must ensure responsible AI practices.

Alternative Real-Life Example: Noise Cancellation

ANN can also be used for:

- Removing background noise in calls
- Speech enhancement

Structure:

- Recurrent Neural Networks (RNN)
- Adaptive learning rule
- Error minimization

Comparison: Facial Recognition vs Noise Cancellation

Feature	Facial Recognition	Noise Cancellation
Input	Image	Audio signal
ANN Type	CNN	RNN
Output	Identity	Clean audio
Learning	Supervised	Supervised/Adaptive

Future Improvements

- Edge AI deployment
- Real-time recognition
- Bias reduction
- Privacy-preserving learning

Conclusion

Artificial Neural Networks have transformed real-world applications, especially facial recognition systems. By mapping the ANN structure—input layer, convolutional layers, activation functions, pooling, fully connected layers, and output layer—we can clearly understand how machines learn facial features and perform classification.

Using supervised learning with backpropagation and cross-entropy loss, the ANN continuously adjusts its weights to minimize error. Advanced CNN architectures developed by organizations such as Google and Facebook demonstrate the power of deep learning in solving complex visual recognition problems.

In summary, modeling ANN in real-life applications like facial recognition shows how biological neuron-inspired systems can solve sophisticated computational problems with high accuracy. Understanding neuron types, architecture, and learning laws provides strong foundational knowledge for developing intelligent systems.