# **CHAPTER 2: METHODOLOGY**

## 2.1 Convolutional Neural Networks

The BhavAI project for emotion detection employs deep learning techniques to classify facial expressions into seven emotion categories: happiness, sadness, anger, surprise, fear, disgust, and neutral. The methodology consists of the following key steps:

#### 1. Dataset Preparation

- Data Collection: A labeled dataset of facial expressions was used, encompassing diverse samples for robust training.
- Data Preprocessing: Images were resized, normalized, and augmented (using rotations, flips, and brightness adjustments) to improve generalization and address class imbalances.



Fig 1: image preprocessing

#### 2. Model Architecture

- A Convolutional Neural Network (CNN) was developed to extract spatial features from facial images.
- The architecture was optimized to balance depth and complexity, ensuring high performance without overfitting.

Fully connected layers classified images into seven emotion categories: happiness, sadness,
anger, surprise, fear, disgust, and neutral.

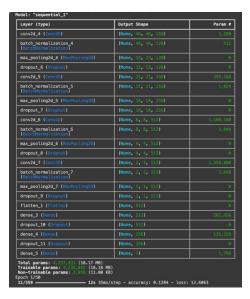


Table 1: CNN layers

## 3. Training Process with Advanced Callbacks

To maximize efficiency and prevent overfitting, intelligent Keras callbacks were incorporated:

- 1. ModelCheckpoint: Automatically saves the best-performing model based on validation accuracy, ensuring the best model version is retained for deployment or evaluation.
- 2. EarlyStopping: Terminates training when validation loss stagnates for a set number of epochs, preventing overfitting and saving computational resources by halting training at the optimal point.
- 3. ReduceLROnPlateau: Dynamically adjusts the learning rate when the validation loss plateaus, facilitating better convergence by fine-tuning learning rates during training.

#### 4. Evaluation Metrics

- Accuracy, Precision, Recall, and F1-Score: Provided insights into overall and class-wise model performance.
- Confusion Matrix: Visualized patterns of misclassification to identify improvement areas.
- Cross-Validation: Ensured model reliability and robustness across different dataset splits.

Fig 2: Test Accuracy

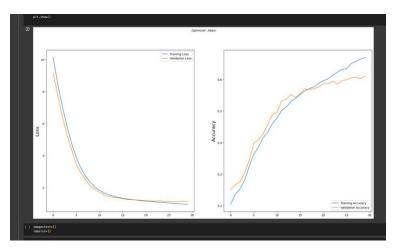


Fig 3: Test accuracy and Loss Graph

# 5. Testing and Results

- The model achieved 87% accuracy on the test set.
- High performance was noted for distinct emotions like happiness, while subtle emotions like fear and sadness showed room for improvement.



Fig 4: Detection Results

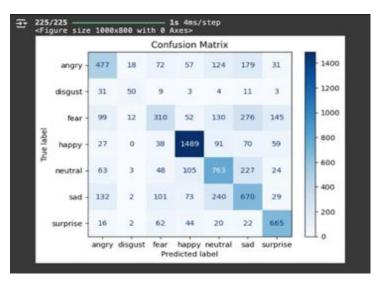


Table 2: Confusion Matrix

#### 6. Future Enhancements

- Extend the model's compatibility to handle coloured (RGB) images effectively, improving its accuracy in real-world scenarios with diverse lighting and backgrounds.
- Implement real-time emotion detection capabilities to enable live video processing and expand its applications in dynamic environments.
- Enhance robustness to work accurately with partial facial occlusions, making the system more versatile for practical use cases.

# 2.2 Website Development

## 1. Frontend Design:

- o A user-friendly web interface was designed using HTML, CSS, and JavaScript.
- o The website includes:
  - Upload Button for users to upload images.
  - A Predict Button for analysing emotions in the uploaded image.
  - Display Area to show uploaded images and prediction results.

### 2. Backend Development:

- A Flask-based Python backend was created to handle image uploads and make predictions.
- The backend performs the following:
  - Image Preprocessing: Resizing and normalizing the uploaded image to match the model's input requirements.
  - Emotion Prediction: The pre-processed image is passed to the trained model, which returns the predicted emotion and its confidence score.

# 3. Integration

- a. Connecting Frontend and Backend:
  - o JavaScript fetch API was used to send the uploaded image to the Flask backend.
  - Prediction results were sent back to the frontend in JSON format and displayed on the website.

#### b. File Management:

 Uploaded images were saved temporarily in a dedicated uploads folder on the server for processing.

#### 4. Deployment

- a. Local Deployment:
  - The Flask app was run locally on http://127.0.0.1:5000/ for development and testing.

o CORS (Cross-Origin Resource Sharing) was enabled to ensure smooth communication between the frontend and backend.

#### b. Hosting Considerations:

 Future deployment to a live server (e.g., AWS, Heroku) can be planned for wider accessibility.

#### 5. User Interaction

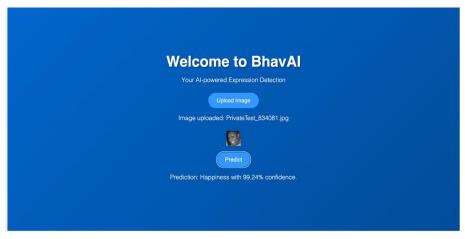
- Users upload an image via the web interface.
- The image is processed, and the predicted emotion is displayed along with a confidence score.
- Additional features include navigation menus, testimonials, and subscription plans to enhance the user experience.

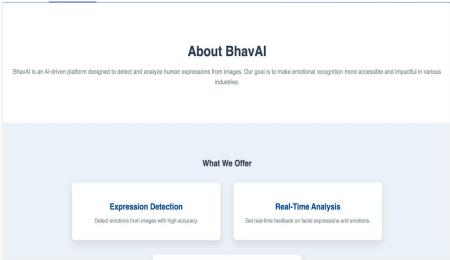
### 7. Styling and User Experience

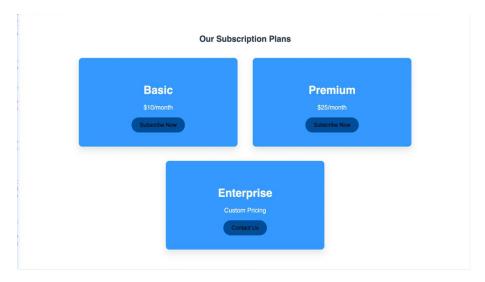
- CSS was used to make the website visually appealing with sections for navigation, services, subscription plans, testimonials, and contact forms.
- A blue gradient theme and responsive design were implemented to improve aesthetics and usability.

## 8. Challenges and Improvements

- Challenges: Ensuring accurate emotion prediction and seamless integration between frontend and backend.
- Future Improvements: Expanding emotion classes, optimizing model performance, and deploying the application on a cloud platform.







Fig(s) 5: Website Development