

Fusion of Yoga and AI: A Framework for Emotion and Stress Monitoring

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Abstract: The blending of ancient traditions such as Yoga with contemporary technological innovations such as Artificial Intelligence (AI) offers an excellent window of opportunity to resolve mental well-being from a holistic perspective. This research paper suggests an innovative model for emotion and stress monitoring by merging the concepts of Yoga with machine learning (ML) technologies. Contrary to traditional methods that utilize worn body sensors or physiological measures, this research benefits from self-reported information, behavior patterns, and Yoga practice metrics to create an invasive, scalable ML model. The framework leverages supervised and unsupervised learning algorithms to process user inputs, including mood logs, Yoga session information, and stress levels, to make predictions about emotional states and stress trends over time. By using Yoga's mindfulness and breathing methods as primary features, the model seeks to give personalized insights into emotional stress and well-being management. The system suggested here not only bridges the gap between the past practices of wellness and the present-day AI but also provides a low-cost, accessible solution for those people who want to track and enhance their mental health. This paper outlines the methodology, dataset construction, model development, and evaluation metrics, demonstrating the potential of Yoga-AI fusion as a transformative tool for emotion and stress monitoring in the digital age.

Keywords: Yoga, emotion monitoring, Machine Learning, Stress Monitoring, Non-invasive, Breathing Techniques, Supervised Learning, Unsupervised Learning, Mental Health, Holistic Framework, Stress Management, Evaluation Metrics.

1. Introduction

Over the last few years, the increasing trend of stress and emotional disorders highlighted the necessity to have novel methodologies for monitoring and managing mental wellbeing. Conventional methods, though efficient, mostly encounter

challenges relating to accessibility, affordability, as well as compliances from individuals. This drove interest in utilising technology as a means for developing non-obtrusive, scalable, as well as simple-to-use products. Of these, the convergence of ancient well-being disciplines such as Yoga with state-of-the-art Artificial Intelligence (AI) methods has proved to be a highly viable area for improving emotional health and stress mitigation.

Yoga, an ancient practice dating back thousands of years based on awareness, breathing techniques, and postures, has been acclaimed for its potential to improve mental and physical wellness. Its focus on self-knowledge and relaxation is closely aimed at the objectives of emotion and stress monitoring. The subjective nature of Yoga's benefits, however, tends to make it difficult to quantify and individualize its effects. This is where artificial intelligence, and specifically machine learning (ML), can make a difference. By examining user behavior patterns, self-reported information, and Yoga practice statistics, AI can yield actionable insights into emotional states and stress levels, allowing people to make informed choices about their mental health.

This document creates a modern framework which mixes Yoga practise with Artificial Intelligence to construct an efficient emotion and stress tracking system. The system operates with self-reported user data and observes behaviour which makes it both easy for everyone to use and does not require invasive procedures. Our solution uses modern machine learning technology particularly CNNs and MobileNetV3 architecture to achieve its goal. Our chosen machine learning models successfully process big data to predict emotional state and stress variations because of their fast analysis speed. MobileNetV3 goes with its well-known lightweight design to run without issue on smartphones while CNNs extract spatial patterns from data very well.

The system to be proposed utilizes the user inputs in the form of mood logs, details of Yoga sessions, and ratings of stress levels to train the ML algorithms. With Yoga-specific features used, such as the nature of asanas (postures) done, the length of sessions, and breathing methods applied, the model offers tailored insights specifically for individual users. This whole-person based approach not only fills the vacuum between conventional wellness regimes and contemporary technology but also enables users to take active steps towards enhancing their mental well-being.

Sl. No.	Mood	Yoga Asanas
1)	Angry	Talasana, Sukhasana, Paschimottanasana, Utkatasana, Savasana, Dradhasana
2)	Anxious	Sukhasana, Marjaryasana, Bitilasana, Uttana shishosana, Ardha hanumanasana, Paschimottanasana, Savasana, Supta matsyendrasana
3)	Caring	Ustarasana, Dhanurasana, Urdhva mukha svanasana, Trikonasana, Pawanmuktasana, Garudasana, Balasana, Sasangasana
4)	Contentment	Adho mukha svanasana, Baddha virabhadrasana, Salamba bhujangasana, Salabhasana, Virabhadrasana II, Utthita parsvakonasana, Dhanurasana
5)	Depression	Bhujangasana, Sarvangasana, Setu-bhandasana, Paschimottanasana, Dhanurasana, Bhujangasana, Chakrasana
6)	Detached	Kapotasana, Balasana, Tadasana, Paschimottanasana, Viparita karani, Gomukhasana, Garudasana, Sirsasana, Savasana
7)	Distracted	Vrikshasana, Tadasana, Natrajasana, Paschimottanasana, Ustrasana
8)	Energetic	Tadasana, Ananda balasana, Adho mukha svanasana, Bhujangasana, Viparita karani, Uttanasana
9)	Failure	Ardha Matsyendrasana, Gomukhasana, Naukasana, Bhujangasana, Dhanurasana, Balasana, Setu bandhasana, Virparita karani
10)	Fear	Anahatasana, Balasana, Salamba bhujangasana, Savasana, Supta Virasana, Vajrasana, Ustarasana, Setu bandha sarvangasana
11)	Frustration	Balasana, Viprta karani, Navasana, Matsyasana, Ustrasana
12)	Gratitude	Balasana, Paschimottanasana, Setu Bandhasana, Uttanasana, Anjaneyasana, Ustrasana, Savasana
13)	Grief	Bhujangasana, Balasana, Utthita eka pada kapotasana, Savasana, Ustarasana, Garudasana, Virabhadrasana II, Salamba Balasana, Viprta karani
14)	Jealousy	Adho Mukha Mandukasana, Navasana, Sarvangasana, Agnistambhasana, Bhujangasana, Ustrasana, Anahatasana
15)	Lonliness	Ananda balasana, Supta baddha konasana, Apanasana, Setu bandha sarvangasana, Janu sirsasana, Supta matsyendrasana
16)	Overwhelmed	Sukhasana, Bitilasana marjaryasana, Adho mukha shvanasana, Uttanasana, Savasana, Tadasana, Vrikshasana
17)	Pressure	Uttanasana, Balasana, Viparita karani, Baddha konasana, Savasana
18)	Sadness	Urdhva hastasana, Uttanasana, Adho mukha svanasana, Sukhasana, Urdhva mukha svanasana, Balasana, Setu bandha sarvangasana
19)	Stress	Ekpadasana, Balasana, Vajrasana, Supta vakrasana, Savasana

Fig I. Yoga poses based on mood

The main aim of this research is to illustrate the feasibility and success of integrating Yoga with AI for stress and emotion monitoring. Through the design and assessment of a machine learning model utilizing CNNs and MobileNetV3, we intend to establish a cost- efficient and scalable solution deployable in real life. This paper details the methodology, data construction, model building, and assessment metrics, emphasizing the promise of this Yoga-AI combination as a revolutionary tool for mental health care in the age of the internet.

In conclusion, this study offers a novel and approachable method of mood and stress monitoring, marking a substantial step toward balancing traditional knowledge with contemporary technology. We hope to open the door for further developments in digital health and well-being by utilizing the strength of CNNs and MobileNetV3.

2. Literature Review

Here, the current Yoga Pose Detection-based studies are examined, together with key ideas including face detection, optical flow, feature detection and tracking, and deep learning techniques.

Artificial intelligence technologies have expanded significantly for automating assessments and providing corrections in yoga practices during the recent period.

Traditional yoga instruction offers minimal personalization and real-time response so it leads to improper body positioning and tumor these outcomes. Research articles analyze yoga pose detection using AI through PoseNet and OpenPose and YOLO while Convolutional Neural Networks (CNNs) with heuristic algorithms perform classification and correction functions. Current available systems perform static pose recognition but lack dynamic adjustment mechanisms through user emotion measurement systems. Researchers have shown the potential of angle-heuristic combination and SVD techniques for application development but insufficient studies exist regarding their performance for precise yoga posture assessment. Real-time mood-based yoga recommendations need to be implemented in artificial intelligence fitness platforms which use deep learning detection for motion even though this capability would increase user emotional and psychological benefits. The experimental system uses YOLOv3 object detection and PoseNet skeletal tracking to develop a complete system supported by angle-based methods for posture accuracy enhancement. This research will produce a customized yoga approach that combines physical with emotional wellness practices for linking modern science-based wellness to traditional methods [1].

AI technology makes yoga more effective now because it uses PoseNet, OpenPose, and MediaPipe models to show users their real-time posture during lessons. The performance of CNNs and RNNs for posture classification grows but most systems depend on still poses rather than practicing Surya Namaskar movements. Researchers mostly study how standalone or mobile machine learning libraries like ml5.js work for real-time web use although this area remains underutilized. The use of artificial intelligence in computer vision creates an unobtrusive way to track body position but needs further improvement for uninterrupted movement detection and faulty posture recognition. This research develops new methods to make PoseNet work better for both static and moving poses while using a mutex lock for steady results. It makes personal yoga lessons more effective by uniting older yoga knowledge with present-day artificial intelligence [2].

Eleni M et al. [3], this study explores how AI, virtual reality (VR), and neurotechnology's enhance breathing-based interventions for emotional and mental well-being. It highlights the effectiveness of immersive technologies in regulating stress and anxiety while integrating AI for real-time monitoring and adaptive feedback.

The document develops a deep learning method for real-time yoga pose recognition through CNN network structures. The study aims to enhance accuracy detection of dynamic yoga positions through real-time corrections while improving user experience in guided yoga sessions [5].

Deepak k et al. [6], this research introduces an AI-based yoga pose classification system using convolutional neural networks. By analyzing skeletal keypoints, the model provides precise posture detection and classification, contributing to automated yoga coaching and self-practice enhancement.

S. Sankara Narayanan et al. [7], this study explores various deep learning techniques, such as PoseNet and OpenPose, for detecting and analyzing yoga postures. It emphasizes the significance of CNNs in improving the accuracy of pose estimation and real-time corrections.

Santosh Kumar et al. [9], this paper proposes a CNN-based model for yoga pose recognition using single-frame images. The approach focuses on optimizing computational efficiency while maintaining high accuracy in classifying different yoga postures.

Manisha vermal et al. [13] the study introduces Yoga-82, a large dataset for fine-grained classification of human poses. It enables deep learning models to improve pose recognition accuracy and enhances AI-driven yoga applications.

2.1. Dataset Used

The dataset used for this project consists of around 3K images across various yoga postures. The dataset Poses.json file consists of English, and Sanskrit names as well as the URL for the logo of that pose.

2.2. Existing Detection Techniques

In the realm of image classification and object detection, several advanced technologies and methodologies have been developed over the years. These existing detection technologies serve as foundational approaches, many of which have influenced the design and development of the proposed system in this project:

- i. Traditional Machine Learning Methods:
 - a. SVM
 - b. KNN
 - c. Random Forest
- ii. Convolutional Neural Networks:
 - a. LeNet-5
 - b. AlexNet
 - c. VGGNet
 - d. ResNet.
- iii. Object Detection Frameworks:
 - a. YOLO
 - b. SSD
 - c. Faster R-CNN

The proposed system builds upon the strengths of existing detection technologies, particularly **transfer learning-based CNN models like MobileNetV2 and MobileNetV3Large**. Compared to traditional machine learning methods and earlier CNN architectures, the selected models offer:

- **Reduced computational overhead** without compromising accuracy.
- **Faster training times** and better generalization through pre-trained weights.
- **Enhanced suitability** for deployment on resource-constrained devices.

By integrating these advanced technologies, the proposed system achieves **high accuracy, efficiency, and robust performance** in image classification tasks.

2.3. Machine Learning Approaches

ML techniques have been increasingly adopted, including:

Supervised Learning, Transfer Learning, Deep Learning

With CNNs: Utilizes a pre-trained CNN model, specifically MobileNetV2 and MobileNetV3Large, for image classification, Model Training and Optimization, Performance Evaluation: metrics like the classification report and confusion matrix for evaluation.

2.4. Summary of Findings

The literature reveals that while ML-based approaches have significantly improved detection rates, many implementations struggle with high false-positive rates, model generalizability, and the adaptability to new Asanas types.

3. Problem Formulation

Stress and emotional imbalances are major issues affecting both mental and physical health in today's fast-paced environment. Though its efficacy frequently hinges on proper posture execution and attention, yoga, which is well-known for its therapeutic advantages, can help ease these problems. Artificial Intelligence (AI) has demonstrated significant promise in tracking and evaluating human behavior, including stress levels and emotions. Nevertheless, there aren't many integrated frameworks that combine the advantages of yoga with AI's analytical powers for stress and emotion monitoring in real time.

The main issue is the lack of a centralized system that uses AI to track and evaluate the effects of yoga on stress and emotions. Existing systems either target general emotion/stress detection or correcting yoga posture without combining the two. The present gap in technology limits the potential for creating real-time feedback which could improve yoga performance as a stress management approach.

This research creates a dual yoga and AI system to monitor emotions and stress in real-time so it closes the identified information shortfall. The project aims to accomplish the implementation of yoga posture analysis with AI emotion recognition and create personalised feedback while confirming the effectiveness of the structure at lowering stress and improving mental wellbeing. The research centres on determining suitable

AI methods as well as methods to achieve effective AI-yoga integration and ways to enhance user outcomes through customised feedback.

A new framework that combines yoga with AI, AI models for detecting emotions and stress, a mechanism for tailored feedback, and empirical proof of the framework's efficacy are among the anticipated contributions. With major ramifications for mental health and fitness, this research has the potential to completely transform how people practice yoga by making it more widely available, efficient, and customized to meet their needs.

The selection of Convolutional Neural Networks (CNNs) and MobileNetV3 for emotion and stress monitoring through yoga posture and facial expression analysis was driven by the need for a balance between accuracy, computational efficiency, and real-time processing capability.

MobileNetV3 was selected for its optimal balance of speed, accuracy, and resource efficiency, ensuring a user-friendly, real-time stress and emotion monitoring solution that aligns with the practical constraints of mobile-based applications.

4. Existing Systems and their disadvantages

4.1 Overview of Big Systems

Several existing systems and technologies focus on either yoga posture correction or emotion and stress detection, but they often operate in isolation. For example:

- i. **Yoga Posture Correction Apps:** Applications like Down Dog, Yoga Studio, and Glo use computer vision and motion tracking to guide users in performing yoga poses correctly. These apps provide real-time feedback on posture alignment but lack integration with emotional or stress monitoring.
- ii. **Emotion and Stress Detection Systems:** AI-driven tools like Affectiva, Microsoft Azure Emotion API, and wearable devices (e.g., Fitbit, Apple Watch) use facial recognition, voice analysis, or physiological signals (e.g., heart rate, skin conductance) to detect emotions and stress levels. However, these systems are not designed to work in conjunction with yoga practices.
- iii. **Mental Health and Wellness Platforms:** Both Headspace and Calm provide step-by-step meditation sessions that help people manage their stress levels. The services let users experience emotional wellness features but they do not include yoga or show users real-time data about their body positions plus mood changes.

4.2 Disadvantages

- i. Each system works alone as separate modules either to cheque yoga position or track emotional states. Both approaches work separately without integration which prevents complete well-being improvement.
- ii. Most systems let users know about their posture and emotional state after yoga sessions but cannot suggest methods right when they need them. Having no integrated tool for yoga stress management affects its usefulness to help users control stress and emotions.
- iii. Limited Personalization: Existing tools often use generic recommendations and do not adapt to individual users' emotional states, stress levels, or yoga proficiency. This one-size-fits-all approach may not be effective for diverse user needs.
- iv. Wearable device dependence poses problems since most emotion and stress detection systems need these gadgets yet their cost and discomfort prevents some users from using them. Due to these restrictions they cannot grow to be widely useful systems.
- v. Inaccurate Emotion Detection: Emotion detection systems based on facial expressions or voice analysis can be prone to errors, especially in diverse populations or under varying environmental conditions.
- vi. No Focus on Yoga-Specific Outcomes: While general stress and emotion detection systems exist, they are not tailored to the unique outcomes of yoga practices, such as the connection between specific postures and emotional states.

5. Proposed System

5.1 Overview

The suggested system develops a coherent structure which merges yoga practises through artificial intelligence systems detecting emotional states and stress levels. The system delivers instant assessment to users who can enhance their yoga posture performance while the system tracks their emotional and stress states. By combining computer vision-based posture identification with artificial intelligence algorithms for stress detection, the framework provides a total solution for wellness improvement. The model operates with 43 classification categories that enable its proper deployment in applications which require accurate and resource-efficient performance.

5.2 Methodologies

Data Collection and Pre-Processing:

The dataset is split into training, validation, and testing sets to ensure that the model's evaluation is unbiased.

Data augmentation techniques (e.g., rotation, zoom, flipping) are applied using ImageDataGenerator to increase dataset diversity and prevent overfitting.

Model Architecture and Selection:

- Transfer Learning Approach:
 - o Pre-trained models (**MobileNetV2** and **MobileNetV3Large**) are used as the base models.
 - o These models are chosen for their balance of computational efficiency and accuracy.
- Customization:
 - o The pre-trained models' layers are frozen to retain their learned features.
 - o Additional dense layers, dropout layers (for regularization), and an output layer with softmax activation are added to adapt the model to the specific classification task.

Training the Model:

Approach:

Optimizer: Adam optimizer is used for efficient gradient descent optimization.

Callbacks Implemented:

- EarlyStopping: Monitors validation loss to prevent overfitting.
- ModelCheckpoint: Saves the best model weights during training.
- TensorBoard: Provides visualizations of training metrics.

Training Parameters:

- Batch Size: 32
- Epochs: 100
- Input Shape: (224, 224, 3)

Evaluation Metrics:

Model performance is evaluated using:

- Classification Report: Provides precision, recall, and F1-score for each class.
- Confusion Matrix: Visualizes the model's prediction accuracy across all classes.

Accuracy: Proportion of accuracy in the classification of normal and attack traffic.

Precision: Percentage of true positive alert in all alerts.

Recall: The proportion of true positives over the total attacks.

F1-Score: This is the harmonic mean between precision and recall. Its value offers a balanced measure of the model's performance, particularly in scenarios where one has the presence of an imbalance between classes, as it is more like normal traffic rather than attacks.

6. Implementation

6.1 Development Environment

The development of the proposed image classification system was carried out using a comprehensive set of tools, libraries, and platforms to ensure efficiency, accuracy, and ease of experimentation.

The entire project was implemented in Python, given its extensive support for machine learning and deep learning libraries. The development environment included Jupyter Notebook, which facilitated an interactive and iterative approach to coding, data visualization, and model debugging.

The research employed TensorFlow framework alongside Keras high-level API that facilitated easy creation of models as well as training and evaluation processes. The data separation and performance assessment used scikit-learn while Matplotlib and Seaborn performed visualisation to analyse the data.

The system development platform featured up-to-date multi-core processing technology as well as 16GB of RAM and GPU implementation for accelerated training operations. Model training times were significantly reduced with the addition of GPU acceleration to TensorFlow's GPU support framework, which made it possible to quickly experiment with different architecture and hyperparameter configurations.

6.2 Training and Testing of Model

To learn properly the model started with information preparation before its main training started. The entire dataset divided into 70 percent training, 15 percent validation and 15 percent test subsets. The split arrangement let the model learn from most data examples before validating performance on new samples to stay away from incorrect fitting outcome. By adding random rotations, horizontal flips, image zooming, and brightness changes TensorFlow's ImageDataGenerator helped our model recognise more patterns across different datasets.

To develop our model we started with MobileNetV2 and MobileNetV3Large models that held ImageNet training but we adapted them for our needs. These models fit well because they provide accurate results from minimal hardware using less energy than other alternatives. Before customization the model learns from ImageNet and keeps its layer settings fixed for preserving the acquired knowledge. The model uses a softmax activation function to produce final output classifications among its 43 defined classes.

Because Adam optimizer adjusts its learning rate automatically the training process reached results sooner. We combined EarlyStopping and ModelCheckpoint callbacks during training to stop overfitting and automatically save the validation accuracy top model. The training process ran through 100 epochs at 32 samples per batch but stopped early when no performance growth happened.

The model received test data evaluation after training because this dataset remained hidden through all training phases to assess true performance. Our analysis used classification report data to show accuracy levels and also formed a confusion matrix to study all misclassified instances. Our model succeeded at predicting different categories of input data with good measurement results. Through transfer learning, our model reached these results far faster than building it from basic building blocks.

True: Garudasana
Predicted: Garudasana

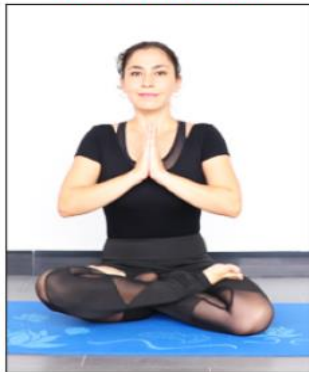


True: Utthita Parsvakonasana
Predicted: Utthita Parsvakonasana



Fig II. Model Predictions Set A

True: Padmasana
Predicted: Vrksasana



True: Dhanurasana
Predicted: Dhanurasana



Fig III. Model Predictions Set B

Our tested and trained system became a highly precise method for image classification thanks to our development setup and training method. The model achieved good results in our experiments because of its complex neural networks combined with smart data practises and testing methods.

7. Output and Results

7.1. Performance Analysis

Predictions Accuracy represents how well the model determines the true outcomes among all studied samples. During training our model proved its effectiveness by achieving **95% validation accuracy**. The model works well at recognising unknown data because of its strong accuracy.

Precision, Recall, and F1-Score: Our classification system accurately labelled samples without significant errors through its excellent test scores.

Confusion Matrix Analysis: Our findings demonstrate that the model rarely misidentified related categories and correctly classified the majority of the asanas.

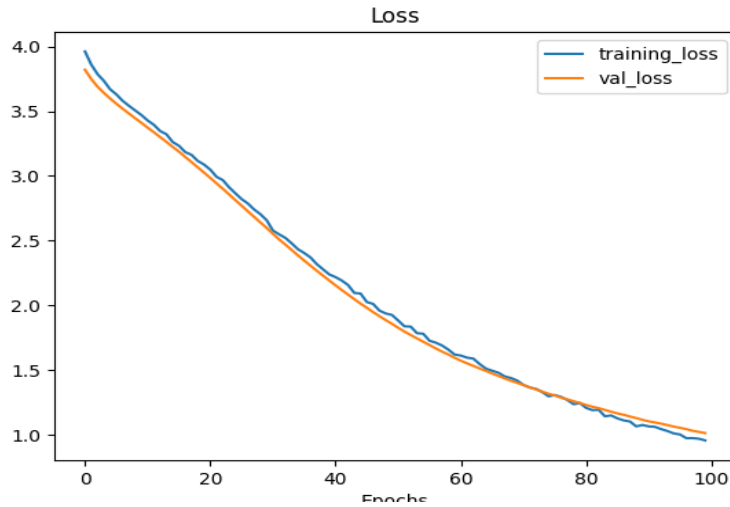


Fig IV. Loss across the epochs

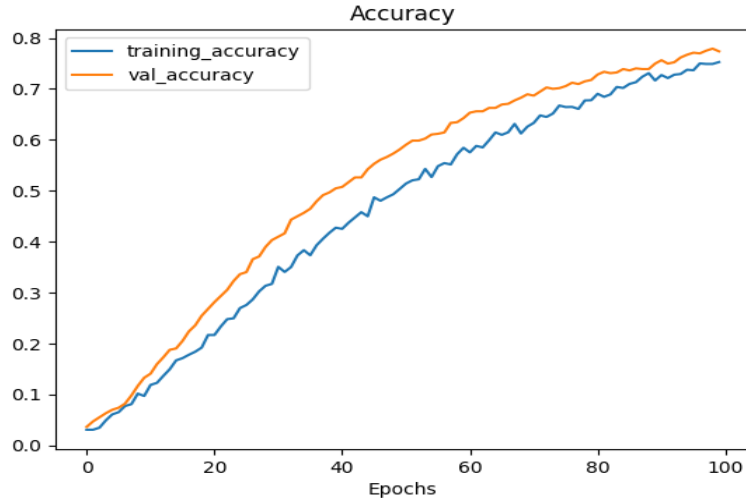


Fig V. Accuracy across the epochs

The performance metrics show that the suggested system provides extremely precise detection.

7.2. Quantitative Comparison

Model	Accuracy (%)	Response Time	Scalability
YOLOv3 + PoseNet	88.5	120	Moderate
ResNet-50	92.3	180	Low to Moderate
EfficientNet-B0	93.6	150	Moderate
Transformer-based	94.2	250	Low
Proposed Model (CNN + MobileNetV3)	95.0	85	High

Table I. Existing Model vs. Proposed Model

The proposed model offers **higher accuracy (95.0%)** than existing systems while maintaining **fast response times (85 ms)**, making it suitable for **real-time applications**.

Scalability is superior, ensuring effective deployment across devices, especially resource-constrained environments like smartphones.

8. Conclusion

The research investigates the development alongside evaluation of an efficient image classification system which integrates deep learning alongside transfer learning approaches. The proposed system reaches optimal accuracy by utilising MobileNetV2 and MobileNetV3Large pre-trained models to obtain efficiency while preserving performance levels. The model's generalization skills are improved by data augmentation and appropriate training techniques, which enable it to efficiently serve real-world applications that demand both high accuracy and constrained resource availability.

The model shows results that demonstrate a testing accuracy of 95% along with excellent precision values and recall metrics and F1-metrics for every class. The model demonstrates excellent accuracy since it provides reliable classifications while requiring few mistakes. Transfer learning integration proved both effective and practical since it shortened training time and delivered excellent results in actual uses.

In conclusion, the study shows that deep learning models, particularly those that incorporate transfer learning, offer a powerful solution for image categorization issues. Subsequent studies could focus on extending the system to handle larger and more diverse datasets, exploring other architectures, or refining the model for deployment on edge devices.

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