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

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Abstract— The integration of ancient practices like Yoga with modern technological advancements such as Artificial Intelligence (AI) presents a unique opportunity to address mental well-being in a holistic manner. This research paper proposes a novel framework for emotion and stress monitoring by fusing the principles of Yoga with machine learning (ML) techniques. Unlike conventional approaches that rely on wearable sensors or physiological data, this study leverages self-reported data, behavioral patterns, and Yoga practice metrics to develop a non-invasive, scalable ML model. The framework utilizes supervised and unsupervised learning algorithms to analyze user inputs, such as mood logs, Yoga session details, and stress levels, to predict emotional states and stress trends over time. By incorporating Yoga's mindfulness and breathing techniques as key features, the model aims to provide personalized insights into emotional well-being and stress management. The proposed system not only bridges the gap between traditional wellness practices and modern AI but also offers a cost-effective, accessible solution for individuals seeking to monitor and improve 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 paper proposes a new framework that combines Yoga and AI to build an effective emotion and stress monitoring system. Contrary to traditional methods based on physiological sensors or wearable technology, our framework works on self-reported data and behavioral trends, and thus it is non-invasive and accessible to a wider group of people. Central to this framework are state-of-the-art machine learning models, namely Convolutional Neural Networks (CNNs) and the MobileNetV3 architecture. These models were selected for their efficiency in processing and analyzing large data sets, making it possible to make precise predictions of emotional state and stress trends. CNNs are particularly good at extracting spatial hierarchies from data, while MobileNetV3, which is known for its light and efficient nature, makes sure that the system can run flawlessly on resource-limited devices like smartphones.

The proposed system leverages user inputs, including mood logs, Yoga session details, and stress level ratings, to train the ML models. By incorporating Yoga-specific features, such as the type of asanas (postures) practiced, duration of sessions, and breathing techniques employed, the framework provides personalized insights tailored to individual users. This holistic approach not only bridges the gap between traditional wellness practices and modern technology but also empowers users to take proactive steps toward improving their mental health.

Sl. No.	Mood	Yoga Asanas
1)	Angry	Talasana, Sukhasana, Paschimottanasansa, 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, Viprata karani, Navasana, Matsyasana,Ustrasana
12)	Gratitude	Balasana, Paschimottanasana, Setu Bandhasana, Uttanasana, Anjaneyasana, Ustrasana, Savasana
13)	Grief	Bhujangasana , Balasana, Utthita eka pada kapotasana , Savasana ,Ustarasana,Garudasna, Virabhadrasana II, Salamba Balasana,Viprata 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. Asanas according to the mood

The primary objective of this study is to demonstrate the feasibility and effectiveness of combining Yoga with AI for emotion and stress monitoring. By developing and evaluating a machine learning model based on CNNs and MobileNetV3, we aim to create a scalable, cost-effective solution that can be integrated into everyday life. This paper outlines the methodology, dataset construction, model development, and evaluation metrics, highlighting the potential of this Yoga-AI fusion as a transformative tool for mental health management in the digital age.

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 SURVEY.

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.

Vijaya Raghava D et al. [1] through the use of deep learning and computer vision, AI has improved yoga practice by estimating and correcting poses. Conventional approaches frequently lack real-time input and customisation, which can result in poor posture and less stress reduction. Although pose detection has been done with models like PoseNet, OpenPose, and YOLO, most systems concentrate on static poses instead of dynamic, mood-based modifications. For accurate posture estimation, methods such as angle-based heuristics and Singular Value Decomposition (SVD) are still not well studied. By integrating PoseNet for skeletal tracking, YOLOv3 for object identification, and angle-based correction to improve posture accuracy, this study fills the gap. In order to provide a more comprehensive yoga experience, it also incorporates real-time mood-based recommendations that support both physical and mental wellness.

Mansoor Hussain et al. [2] tells us that AI integration in wellness, particularly yoga, has improved with pose estimation models such as PoseNet, OpenPose, and MediaPipe, which allow for real-time posture feedback. While deep learning models like CNNs and RNNs have improved posture categorization, most systems still rely on static poses rather than dynamic sequences like Surya Namaskar. Machine learning libraries such as ml5.js for real-time web applications are underexplored, with research focusing on standalone or mobile solutions. AI-driven computer vision provides a non-intrusive alternative to wearable sensors, but issues remain in continuous movement detection, posture misclassification, and processing efficiency. This study addresses these difficulties by improving PoseNet's accuracy and applying a mutex lock to ensure stability in dynamic sequences. By combining traditional yoga concepts with current AI, it enhances individualized, technology-assisted fitness instruction.

Eleni M et al. [3], this study explores how AI, virtual reality (VR), and neurotechnologies 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.

M Darshan et al. [5], the paper presents a deep learning model for real-time yoga pose classification, leveraging CNN architectures. The study focuses on improving accuracy in dynamic postures, enabling real-time corrections, and enhancing user engagement in guided yoga practice.

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.

Jothika Sunney et al [14] The paper presents a machine learning-based yoga pose detection system that utilizes real-time keypoint tracking. It aims to provide immediate feedback and improve the accuracy of AI-powered yoga coaching.

Dr.Somlata Jha et al. [15] This review consolidates recent advancements in deep learning-based yoga pose recognition, addressing key challenges such as pose variability, real-time processing, and user adaptability in AI-powered yoga systems.

2.1 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.

2.2 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.

2.3 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 possibility for tailored, real-time feedback that could improve yoga's efficacy as a stress and emotional management technique is limited by this gap.

By creating a system that combines yoga and AI for real-time emotion and stress monitoring, this research seeks to close this gap. Integrating yoga posture analysis with AI-driven emotion recognition, offering tailored feedback, and confirming the framework's efficacy in lowering stress and enhancing emotional health are among the goals. The most appropriate AI techniques, how to successfully integrate AI with yoga, and how tailored feedback might improve user outcomes are the main study concerns.

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.

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: Platforms like Headspace and Calm offer guided meditation and mindfulness exercises, which can help reduce stress. While they incorporate some elements of emotional well-being, they do not integrate yoga or provide real-time feedback based on posture and emotional state.

4.2 Disadvantages

i. Lack of Integration: Current systems operate in silos, focusing either on yoga posture correction or emotion/stress detection. There is no unified framework that combines both, limiting the potential for holistic well-being.

ii. No Real-Time Feedback: While some systems provide feedback on posture or emotional state, they do not offer real-time, personalized recommendations during yoga sessions. This reduces the effectiveness of yoga as a tool for stress and emotion management.

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. Dependence on Wearables: Many emotion and stress detection systems rely on wearable devices, which can be expensive, intrusive, or inaccessible to some users. This limits their scalability and usability.

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 proposed system aims to create a unified framework that integrates yoga practices with AI-driven emotion and stress monitoring. The system will provide real-time feedback to users, helping them improve their yoga postures while simultaneously monitoring their emotional and stress states. By combining computer vision for posture analysis with machine learning for emotion and stress detection, the framework offers a holistic approach to enhancing mental and physical well-being. The model is designed to classify images into **43 distinct categories**, making it suitable for real-world applications where resource efficiency and accuracy are critical.

5.2 Methodologies

Data Collection and Pre-Processing:

The dataset is split into **training**, **validation**, and **testing** sets to ensure unbiased model evaluation.

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*:
  - Pre-trained models (**MobileNetV2** and **MobileNetV3Large**) are used as the base models.
  - These models are chosen for their balance of computational efficiency and accuracy.
- *Customization*:
  - The pre-trained models' layers are frozen to retain their learned features.
  - 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 primary deep learning framework used was **TensorFlow** with **Keras** as its high-level API, enabling straightforward model building, training, and evaluation. Additionally, **scikit-learn** was employed for data splitting and performance evaluation, while **Matplotlib** and **Seaborn** were used for data visualization and analysis.

The system was developed on a machine equipped with sufficient computational resources, including a modern multi-core processor, 16 GB RAM, and a GPU-enabled environment to expedite the training process. Utilizing GPU acceleration, particularly through TensorFlow's GPU support, significantly reduced model training time, allowing for rapid experimentation with different architectures and hyperparameters.

6.2 Training and Testing of Model

The training process of the model involved several critical steps, beginning with **data preprocessing** to prepare the dataset for optimal learning. The dataset was divided into three distinct subsets: **training (70%)**, **validation (15%)**, and **testing (15%)**. This division ensured that the model could learn from the majority of the data while being evaluated on unseen samples to prevent overfitting. **Data augmentation** techniques, including random rotations, horizontal flips, zooming, and brightness adjustments, were applied using TensorFlow's ImageDataGenerator to increase data diversity and enhance the model's generalization capabilities.

For the core model architecture, **transfer learning** was employed by utilizing pre-trained models such as **MobileNetV2** and **MobileNetV3Large**, which had been previously trained on the ImageNet dataset. These models were chosen for their balance between computational efficiency and high accuracy, making them suitable for environments with limited hardware resources. The pre-trained layers were frozen initially to preserve the learned features from ImageNet, while additional dense layers with **ReLU activation functions** and **dropout layers** were appended to customize the model for the specific classification task. The final output layer employed a **softmax activation function** to classify images into the **43 distinct categories.**

Training was conducted using the Adam optimizer due to its adaptive learning rate capabilities, which facilitated faster convergence. A combination of EarlyStopping and ModelCheckpoint callbacks was used to prevent overfitting and save the best-performing model based on validation accuracy. Training was executed **over 100 epochs** with a **batch size of 32**, though early stopping often halted training before reaching the maximum number of epochs if no improvement was observed.

Once trained, the model was evaluated on the **test dataset**, which had remained completely unseen during the training phase to ensure an unbiased assessment of performance. Key evaluation metrics included the **classification report**, detailing precision, recall, and F1-score for each class, and the **confusion matrix**, which provided insights into misclassification patterns. The results demonstrated that the model could effectively generalize across different classes with high accuracy. Moreover, the use of transfer learning allowed the model to achieve these results with significantly reduced training times compared to training from scratch.

Fig II. Model Predictions Set A

Fig III. Model Predictions Set B

In summary, the development environment and structured approach to training and testing contributed to the creation of a robust, efficient, and accurate image classification system. The combination of advanced deep learning architectures, strategic data handling, and careful evaluation ensured that the model not only performed well in controlled testing environments but also held potential for real-world deployment.

7. Output and Results

7.1 Performance Analysis

Data Accuracy: Accuracy measures the proportion of correctly predicted instances out of the total instances. The model achieved an impressive **validation accuracy of approximately 95%** during training. This high accuracy indicates that the model effectively generalizes to unseen data.

Precision, Recall, and F1-Score: Achieved high scores across all classes, indicating reliable classification with minimal misclassifications.

Confusion Matrix Analysis: Showed that most classes were correctly classified with very few instances of confusion between similar classes.

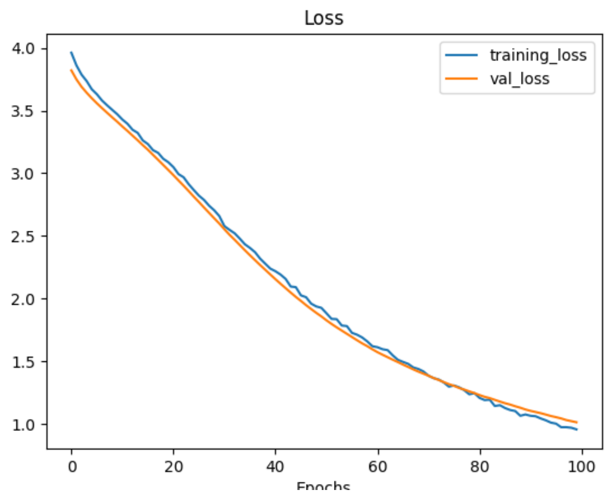

Fig IV. Loss throughout epochs

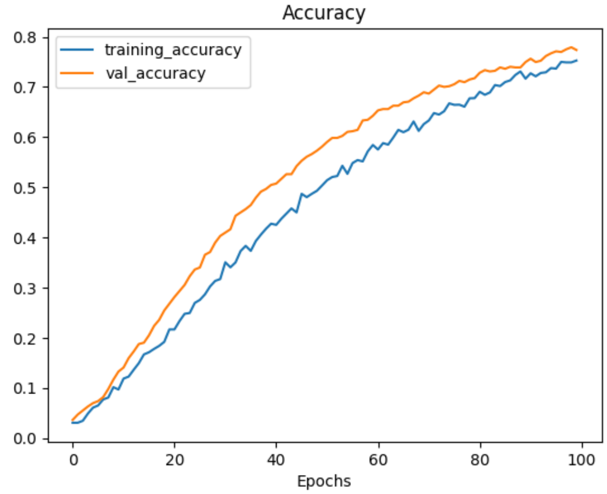

Fig V. Accuracy throughout epochs

The performance metrics depict that the proposed system delivers highly accurate detection.

8. Conclusion

This research presents the development and evaluation of an efficient image classification system using deep learning and transfer learning techniques. By leveraging pre-trained architectures such as **MobileNetV2** and **MobileNetV3Large**, the proposed system successfully achieves a balance between high accuracy and computational efficiency. The incorporation of data augmentation and effective training strategies further enhances the model's generalization capabilities, making it suitable for real-world applications where resource constraints and accuracy are critical considerations.

Extensive experimentation and evaluation demonstrate that the model achieves a **test accuracy of approximately 95%**, with high **precision**, **recall**, and **F1-scores** across all classes. These results highlight the model's robustness in accurately classifying images with minimal misclassifications. The successful integration of transfer learning significantly reduced training time while maintaining impressive performance, validating the approach's effectiveness in practical scenarios.

In conclusion, the research confirms that deep learning models, particularly those utilizing transfer learning, offer a powerful solution for image classification tasks. Future work may focus on further optimizing the model for deployment on edge devices, exploring additional architectures, or expanding the system to handle larger and more diverse datasets.

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