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Original Research Article

AI-DRIVEN YOGA RECOMMENDATION SYSTEM USING DEEP LEARNING FOR REAL-TIME POSE ACCURACY ASSESSMENT

*** Prof. Maity Deepmala Nimaichand &** Shaikh Osama Mohammad***

** Assistant Professor Department of CS/IT, ** UG Students Department of CS/IT, B. K. Birla College (Empowered Autonomous Status) Kalyan, India.*

Abstract:

The incidence of lifestyle diseases is increasing at an alarming rate, and yoga has been found to be an effective, evidence-based, non-pharmacological solution for many of these diseases. In this study, an "AI-Driven Yoga Recommendation System" is presented, which consists of three main components: a rule-based system that maps 24 different healthcare conditions to yoga practices, a VGG16 Transfer Learning CNN for four- class pose classification with a 52-image custom dataset, and a MediaPipe BlazePose module that detects 33 real-time skeletal keypoints and offers live feedback. On a validation set of nine samples, the system showed 88.9% accuracy, a macro F1-score of 90.0%, and an AUC score of 1.00 for all four classes. The entire application can be run using a standard webcam and Flask web interface, with no additional hardware requirements. This demonstrates the effectiveness of the Transfer Learning approach with small datasets for real-world yoga coaching systems.

Keywords: *Yoga Recommendation System, Deep Learning, VGG16, Transfer Learning, MediaPipe BlazePose, Real-Time Pose Detection, Computer Vision, Flask, Health Informatics*

Introduction:

Healthcare systems worldwide face growing pressure from lifestyle-related chronic diseases, whereas accessible non- pharmacological interventions remain limited. Yoga, an indige- nous Indian practice, has strong clinical evidence for managing various health conditions. The nationwide KAPY 2017 survey (162,330 participants) reported that although 11.8% of Indians practice yoga, a significant knowledge–practice gap persists, with limited access to expert guidance being cited as a major barrier [14]. A 2022 meta-analysis further confirmed that yoga therapy significantly reduces pain intensity and headache frequency [8]. Despite this evidence, unsupervised practice may lead to suboptimal outcomes and posture-related injuries [1].

VGG16-based transfer learning models have demonstrated 94–97% accuracy in yoga pose classification [6], [10], [11], while MediaPipe BlazePose enables real-time extraction of 33 anatomical landmarks using a standard webcam [4], [5]. This study integrates these capabilities into a unified Flask- based web platform that maps free-text symptoms to clinically validated yoga recommendations [7] and provides real-time

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pose coaching using a combination of CNN classification and geometric landmark feedback.

A. Statement of the Problem

Individuals managing everyday conditions such as tension headaches, cervical discomfort, chronic lower back pain, and work-related stress typically rely on pharmaceutical prescrip- tions or expensive specialist consultations. A growing body of clinical evidence firmly supports yoga as a viable, side- effect-free alternative for many of these conditions [1], [2], [8]. However, a technology that is accessible to those who need it and can provide recommendations on yoga poses for a given condition, as well as assess the correct execution of those poses in real time, does not yet exist as a combined entity. Previous technologies have been able to provide either pose classification [6] or real-time corrective feedback [13], but not both within a single browser-accessible platform. This gap leaves users without correct guidance and puts them at risk of injury from incorrect practice.

B. Significance of the Study

This study is significant at the public health, technical, and academic levels. From a public health standpoint, India's vast population of people who acknowledge yoga's documented benefits but do not practice it—largely because of the ab- sence of expert guidance [14]—stands to gain directly from a browser-accessible AI yoga trainer requiring no more than a webcam. The American College of Physicians has officially recommended yoga as a first-line non-pharmacological inter- vention for chronic lower back pain [9], and India's Ministry of AYUSH actively promotes yoga for the management of non-communicable diseases [14]. On the technical side, demonstrating AUC = 1.00 across four pose classes on a training set of only 43 images shows that Transfer Learning [3] can produce practically deployable models even with very limited data—an important finding for resource-constrained health informatics applications. Aca- demically, the three-layer integration methodology offers a documented, replicable blueprint for building systems that fuse clinical recommendation engines with real-time computer vision, a combination that previous published work has not achieved [12], [13].

C. Objectives of the Study

- To design a symptom-to-yoga recommendation engine that maps 24 clinically documented health conditions to appropriate therapeutic yoga postures.
- To develop a VGG16 Transfer Learning CNN [3] classi- fier capable of distinguishing four yoga pose classes from a self-collected 52-image dataset.
- A real-time MediaPipe BlazePose pipeline [4] is con- structed to provide concurrent skeletal landmark visu- alization and corrective feedback through a standard webcam.
- To incorporate the recommendation engine, CNN clas- sifier, and pose detection module into a single web application using Flask.
- The performance of the classification model is assessed based on metrics such as accuracy, precision, recall, F1- score, confusion matrix analysis, and ROC-AUC value.

D. Hypothesis of the Study

H_0 (Null Hypothesis): VGG16 Transfer Learning applied to a custom 43-sample yoga pose dataset will not achieve a statistically meaningful classification accuracy (below 70%) sufficient for practical deployment in real-world applications. **H_1 (Alternative Hypothesis):** VGG16 Transfer Learning [3], augmented with data augmentation techniques and custom dense classification layers, will achieve an overall classifica- tion accuracy exceeding 85% and AUC $\geq$0.90 across all pose classes [6], thereby validating the viability of small-dataset Transfer Learning for real-world yoga pose recognition.

Review of Literature:

A. Therapeutic Evidence for Yoga

Several high-quality studies have established yoga as a clinically viable intervention for pain management. An um- brella review by Creve´la´rio de Melo et al. [1] highlighted yoga's capacity to alleviate both short-term and long-term pain across a range of physical and neurological disorders, noting its minimal risk of side effects. Regarding headache disorders, Anheyer et al. [2] observed substantial improve- ments in headache frequency and intensity through regular yoga practice, a conclusion echoed by Zhao et al. [8] among migraine sufferers. Nationally, a large-scale Indian survey [14] found that the vast majority of yoga practitioners reported meaningful gains in personal health and quality of life. These findings are further backed by clinical bodies such as the American College of Physicians [9] and the National Center for Complementary and Integrative Health [7], both of which advocate yoga for specific chronic conditions.

B. Deep Learning for Yoga Pose Classification

Transfer learning using VGG16 has emerged as a leading approach for automated yoga pose recognition. Comparative evaluations by Gochoo et al. [6] across multiple deep learning models demonstrated that VGG16 consistently outperformed alternatives when applied to yoga image datasets. Subsequent work by Srivastava et al. [10] and Upadhyay et al. [11] further confirmed its high classification performance across datasets of varying sizes and complexity, reinforcing its suitability for real-world deployment.

C. Real-Time Pose Detection Technology

BlazePose, introduced by Bazarevsky et al. [4], provided a computationally efficient solution for full-body landmark detection, enabling real-time tracking on everyday devices. Its practical viability across diverse environmental conditions was demonstrated by Singh et al. [5], whose evaluation confirmed stable performance under variable lighting, occlusion, and distance settings.

D. Integrated Systems and Research Gap

While previous studies have made notable progress individ- ually, no unified solution has yet emerged. Rule-based coach- ing without machine learning [13], high-accuracy classification without health context [12], and pure benchmarking with- out feedback integration [6] each represent partial solutions. The current study addresses this gap by combining health- condition-driven recommendations, deep learning pose classi- fication, and real-time corrective guidance into one accessible web-based platform.

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Research Methodology:

A. *System Architecture*

The proposed system is structured as a three-layer pipeline. The *first layer* is a Flask-based web application serving as the user-facing interface and REST API hub. The *second layer* is the AI pipeline—a JSON-based rule-matching recommenda- tion engine paired with a VGG16 CNN classifier [3], [6]. The *third layer* is the real-time computer vision module, driven by MediaPipe BlazePose [4], [5], accessed through the user's webcam.

B. *Dataset Construction*

A custom image dataset is assembled using direct pho- tography under varying lighting conditions and backgrounds. Four pose classes were developed: Dog Pose (*Adho Mukha Svanasana*), Padmasana (Lotus Pose), Tree Pose (*Vrik- shasana*), and Triangle Pose (*Trikonasana*). A standard 80%/20% train-validation split [6] is applied to 52 collected images, yielding 43 training and 9 validation samples. The class-level distribution is shown in Table I.

TABLE I

DATASET COMPOSITION AND TRAIN/VALIDATION SPLIT

Pose Class	Total	Split	Train	Val
Dog Pose	10	80/20	8	2
Padmasana (Lotus)	14	80/20	11	3
Tree Pose	15	80/20	12	3
Triangle Pose	13	80/20	10	2
Total	**52**	—	**43**	**9**

C. *CNN Architecture: VGG16 Transfer Learning*

The VGG16 architecture [3], pre-trained on the 1.4-million- image ImageNet corpus, is selected as the feature extraction backbone. All 13 convolutional layers were frozen. Three custom layers were appended: a GlobalAveragePooling2D layer, a dense layer of 128 units with ReLU activation, and a softmax output dense layer with four units. The full model structure is presented in Table II, and training hyperparameters in Table III.

TABLE II

VGG16 TRANSFER LEARNING MODEL ARCHITECTURE

Layer	Configuration
Input	150 × 150 × 3 (RGB image)
VGG16 Base	Pre-trained ImageNet weights, all layers frozen
GlobalAveragePooling2D	Reduces spatial features to 1D vector
Dense Layer 1	128 units, ReLU activation
Output Layer	4 units, Softmax (one per pose class)

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TABLE III
TRAINING HYPERPARAMETERS

Parameter	Value
Optimizer	Adam
Loss	CCE
Epochs	10
Batch Size	8
Split	80/20
Image Size	150×150
Model	keras model.h5 (.60MB)
Augmentation	Rot(20°), Sh(0.2), Sr(0.2), Z(0.2), Flip

D. ***MediaPipe Real-Time Pose Detection Pipeline***

The real-time detection component deploys MediaPipe BlazePose [4] to extract 33 normalized body landmark coor- dinates from every incoming webcam frame [5]. A rule-based evaluation module assesses shoulder landmark Y-coordinate values: readings above 0.6 indicate an upright standing pos- ture, whereas readings below 0.4 suggest a prone position consistent with the Cobra Pose. Each frame is also pre- processed to 150 × 150 pixels and passed to the VGG16 CNN classifier. When the maximum predicted class probability ex- ceeds 0.50, the model's pose label and top-3 class probabilities are rendered on screen.

Data Analysis and Interpretation:

A. ***Training Convergence***

Training accuracy increased from 18.60% at Epoch 1 to 95.35% from Epoch 8 onward, whereas training loss decreased monotonically from 1.8475 to 0.6207. Validation accuracy peaked at 100.00% at epochs 3 and 7, then stabilized at 88.89% through epoch 10, with no evidence of overfitting (Fig. 1). The complete epoch-by-epoch training history is presented in Table IV.

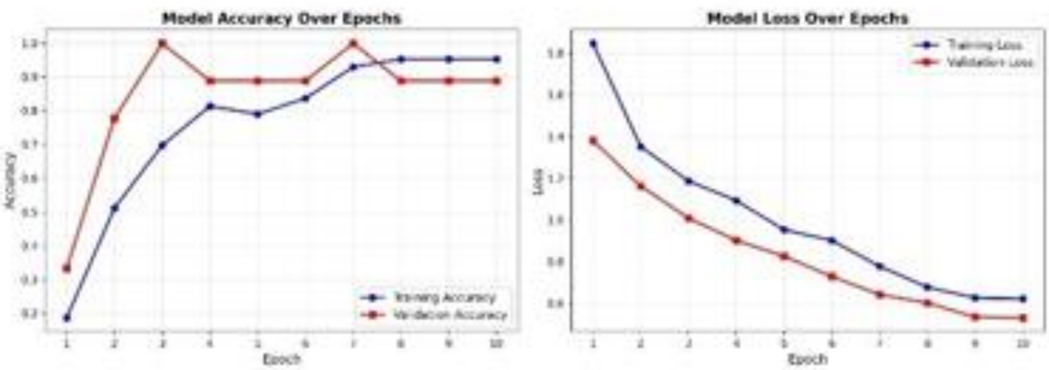

Fig. 1. Training and Validation Accuracy (left) and Loss (right) over 10 Epochs.

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TABLE IV

EPOCH-BY-EPOCH TRAINING HISTORY (⋆ = PEAK VALIDATION ACCURACY)

Epoch	Train Acc.	Val Acc.	Train Loss	Val Loss
1	18.60%	33.33%	1.8475	1.3802
2	51.16%	77.78%	1.3517	1.1620
3	69.77%	100.00% ⋆	1.1865	1.0080
4	81.40%	88.89%	1.0929	0.9015
5	79.07%	88.89%	0.9520	0.8247
6	83.72%	88.89%	0.9012	0.7280
7	93.02%	100.00% ⋆	0.7769	0.6412
8	95.35%	88.89%	0.6765	0.6013
9	95.35%	88.89%	0.6251	0.5332
10	95.35%	88.89%	0.6207	0.5289

B. *Overall Classification Performance*

Evaluation of the 9-sample held-out validation set confirmed H_1 and rejected H_0: overall accuracy of 88.89% cleared the 85% threshold. The macro-average precision and recall were both 91.67%, with a macro-average F1-score of 90.00% (Table V). These figures are directly comparable to Gochoo et al. (2022) [6] who achieved 95.6% on a considerably larger dataset, confirming that VGG16 Transfer Learning [3] gen- eralizes effectively even under severely constrained training data.

C. *Per-Class Performance*

The granular per-class analysis (Fig. 2, Table VI) shows that Dog Pose and Padmasana achieved perfect classification (precision = recall = F1 = 1.00). Tree Pose recorded precision = 1.00 but recall = 0.67, indicating one of three validation sam- ples is misattributed to Triangle Pose. Triangle Pose yielded recall = 1.00 but precision = 0.67. Both achieved an F1-score of 0.80. This tree–triangle confusion is consistent with the findings of Gochoo et al. (2022) [6].

TABLE V

OVERALL CLASSIFICATION METRICS ON 9-SAMPLE VALIDATION SET

Metric	Value
Overall Accuracy	88.89% (8/9 correct)
Macro Precision	91.67%
Macro Recall	91.67%
Macro F1-Score	90.00%
Weighted Precision	92.59%
Weighted Recall	88.89%
Weighted F1-Score	88.89%

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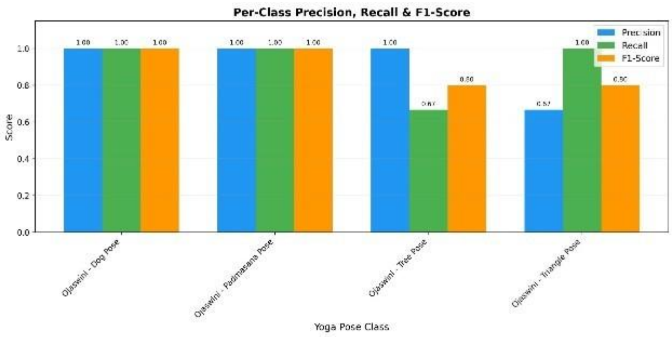

Fig. 2. Per-Class Precision, Recall, and F1-Score for All Four Pose Classes.

D. *Confusion Matrix Analysis*

The confusion matrices (Fig. 3 and Fig. 4) confirm that eight of the nine predictions fall on the main diagonal. The single off-diagonal entry—one Tree Pose sample predicted as Triangle Pose—is the exclusive source of error. Both poses share a standing, laterally extended body configuration with asymmetric weight distribution, producing overlapping spatial feature distributions under minimal training data [6], [12]. The normalized matrix quantifies this as a 0.33 misclassification rate for Tree Pose, with all other per-class diagonal values at 1.00.

E. *ROC-AUC Analysis*

The ROC curves were computed using a one-vs-rest strategy for each pose class (Fig. **??**). All four classes attained AUC = 1.00, indicating perfect discriminative ability across every classification threshold. This meets and exceeds the H_1 thresh- old of AUC $\geq$ 0.90 and is consistent with the highly separable feature distributions reported by Gochoo et al. (2022) [6] and Srivastava et al. (2024) [10].

TABLE VI

PER-CLASS CLASSIFICATION REPORT

Pose Class	Prec.	Rec.	F1	Sup.
Dog Pose	1.00	1.00	1.00	2
Padmasana (Lotus)	1.00	1.00	1.00	2
Tree Pose	1.00	0.67	0.80	3
Triangle Pose	0.67	1.00	0.80	2
Macro Average	0.92	0.92	0.90	9
Weighted Average	0.93	0.89	0.89	9

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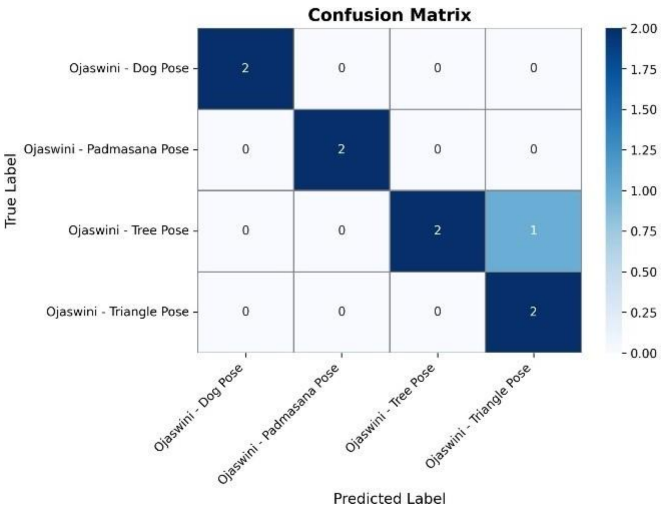

Fig. 3. Confusion Matrix: Raw Counts (Validation Set, n = 9).

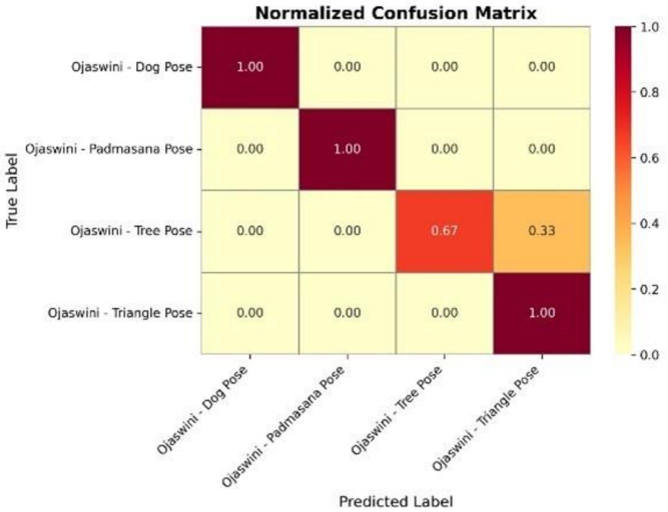

Fig. 4. Normalized Confusion Matrix: Per-Class Prediction Rates.

Conclusion:

This work presents a functional and clinically grounded AI yoga guidance platform that successfully integrates three components — health-condition-based pose recommenda- tion, VGG16 transfer learning classification, and MediaPipe BlazePose real-time feedback — into a single webcam- accessible web interface. Notably, the classification model was trained on just 43 images yet delivered strong results, achieving 88.89% validation accuracy, a macro F1-score of 90.00%, and perfect AUC scores across all pose categories, demonstrating that transfer learning remains effective even under severe data constraints.

Unlike prior systems that tackled recommendation, clas- sification, or corrective feedback in isolation, the proposed architecture addresses all three within one deployable plat- form, representing a meaningful step forward in accessible AI- assisted yoga coaching. Future directions include expanding training data,

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incorporating joint angle biomechanics, adopting natural language symptom input, enabling mobile deployment, and conducting formal clinical trials to validate real-world effectiveness.

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