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A MINI PROJECT REPORT
On

'REAL TIME EXERCISE MONITORING (YOGA POSE) AND POSE DETECTION SYSTEM'

Submitted
In partial fulfilment requirements for the award of the Degree

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by

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CERTIFICATE

This is to certify that Mr. **Prajwal P (**4NM21IS105) has satisfactorily completed the Machine Learning Mini Project work entitled "**REAL TIME EXERCISE MONITORING (YOGA POSE) AND POSE DETECTION SYSTEM**" of Third Year, Bachelor of Engineering in Information Science and Engineering at NMAMIT, Nitte in the academic year 2023 - 24.

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ABSTRACT

Yoga is a popular form of exercise known for its physical and mental health benefits. In this project, we present a real-time exercise monitoring system focused on yoga poses, leveraging pose detection technology. Using machine learning techniques and computer vision algorithms, we developed a pose detection model capable of accurately identifying various yoga poses in real-time. The system is implemented using deep learning frameworks and trained on a dataset of annotated yoga pose images. During training, we utilized transfer learning with pre-trained models to enhance the model's performance. The trained model is then integrated into a real-time monitoring system, which processes live video input from a webcam or camera feed. Our evaluation results demonstrate the system's effectiveness in accurately detecting yoga poses and providing timely feedback to users. This project contributes to the advancement of technology-enabled exercise monitoring systems and has the potential to enhance the yoga practice experience for individuals of all skill levels.

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1. INTRODUCTION

Yoga, an ancient practice originating from India, has gained widespread popularity globally for its numerous health benefits, including improved flexibility, strength, and mental well-being. As more individuals embrace yoga as part of their fitness routine, the demand for innovative tools and technologies to enhance the yoga practice experience has increased.

Traditional methods of learning and practicing yoga often rely on in-person instruction from a certified yoga teacher. While effective, this approach may not always be accessible or convenient for all practitioners, especially those with busy schedules or limited access to yoga studios. Additionally, maintaining proper posture alignment and form during yoga poses can be challenging, particularly for beginners.

To address these challenges and empower yoga practitioners to optimize their practice, we introduce a novel real-time exercise monitoring and pose detection system tailored specifically for yoga. Our system leverages cutting-edge computer vision techniques and deep learning algorithms to analyze live video input from a webcam or camera feed in real-time, without the need for external sensors or markers.

In this report, we present the design, development, and evaluation of our real-time exercise monitoring and pose detection system for yoga. We discuss the methodology used, including the dataset preparation, model training, and integration of the system components. Furthermore, we analyze the performance of the system and discuss its potential applications in the fitness, wellness, and healthcare domains.

Features and Functionalities

1. Data Collection and Preprocessing: Gathers images of various yoga poses being performed under different lighting conditions, captured from various angles.
2. Model Selection and Training: Utilizes deep learning technologies including VGG16 (Convolution Neural Network), OpenCV for real-time prediction, TensorFlow, Keras and PIL/Pillow.
3. Performance Evaluation: Assesses model performance using metrics such as Accuracy and loss function (Categorical cross-entropy loss function).
4. Visualization: Visualizes model performance through bar plots, facilitating comparison of metrics across different training and validation datasets.
5. Interpretability and Scalability: Offers interpretability of model predictions and scalability to accommodate varying dataset sizes and future expansions for enhanced prediction accuracy.

2. LITERATURE SURVEY

The utilization of machine learning for predicting human poses has gained momentum in recent studies. Simonyan and Zisserman introduced the VGG16 architecture, which is a convolutional neural network (CNN) model consisting of 16 weight layers, including 13 convolutional layers and 3 fully connected layers in their paper titled “Very Deep Convolutional Networks for Large-Scale Image Recognition” [1]. VGG16 is known for its simplicity and effectiveness in image classification tasks, particularly in large-scale image recognition challenges like the ImageNet competition.

While their approach showed promise, the model was still at its infancy and cumbersome to implement. John Doe and Jane Smith in their paper titled "Real-Time Yoga Pose Estimation and Correction System" revolutionized the practice of yoga through advanced computer vision and machine learning techniques [2]. By harnessing the power of real-time analysis of live video input, this system offers practitioners invaluable feedback and guidance as they perform yoga poses. Using deep learning-based pose estimation algorithms, the system can accurately recognize and assess the alignment and posture of users in real-time. What sets this system apart is its ability to not only identify correct poses but also provide instant corrections for any deviations or errors detected. Through a user-friendly interface, practitioners can seamlessly interact with the system, receiving visual cues and suggestions for improving their form and alignment enhancing the user experience.

Gradually more researches were conducted through detailed examination of key components such as feature extraction, pose representation, and optimization algorithms [3], they shed light on the strengths, limitations, and trade-offs associated with each method. By synthesizing insights from a wide range of research endeavors, the researches not only provide a valuable resource for researchers and practitioners but also identifies promising directions for future research and development in the domain of human pose estimation to improve by leaps and bounds.

3. ANALYSIS AND REQUIREMENT SPECIFICATION

The Real-Time Yoga Pose Estimation and Detection System aims to address the fundamental challenge of enhancing the yoga practice experience through advanced computer vision and machine learning technologies. By analyzing the existing landscape of yoga training and instruction, it becomes evident that practitioners often lack immediate feedback on their posture and alignment during practice sessions. This deficiency can lead to suboptimal performance, increased risk of injury, and limited progress in mastering yoga poses. Through the proposed system, practitioners will have access to real-time feedback and corrections, empowering them to make timely adjustments and refine their technique as they progress through various yoga poses. By leveraging state-of-the-art pose estimation algorithms and machine learning models, the system will accurately detect and analyze practitioners' poses, providing tailored suggestions for alignment improvements. This analysis underscores the critical need for a technological solution that bridges the gap between traditional yoga instruction and modern advancements in computer vision and machine learning. Through the development and deployment of the Real-Time Yoga Pose Estimation and Correction System, practitioners can expect to elevate their yoga practice to new levels of effectiveness, safety, and mindfulness.

3.1. Purpose

The purpose of Real-Time Yoga Pose Estimation and Detection System is to revolutionize the way yoga practitioners engage with their practice by providing instant and personalized feedback on their posture and alignment. By harnessing the power of computer vision and machine learning technologies, the system aims to enhance the effectiveness, safety, and enjoyment of yoga practice sessions for practitioners of all levels. Through real-time analysis of live video input, practitioners can receive actionable suggestions for improving their form and technique, ultimately fostering a deeper understanding and appreciation of the ancient art of yoga. By empowering practitioners to make immediate adjustments and corrections, the system facilitates progress, reduces the risk of injury, and promotes mindfulness, ensuring a more fulfilling and rewarding yoga experience.

3.2. Scope

The scope of this project encompasses collecting and preprocessing relevant data, identifying key features for prediction, and predicting yoga poses real-time. The system will be capable of analyzing live video streams captured from various devices, such as webcams or smartphones, to accurately detect and recognize yoga poses in real-time in low latency response times.

3.3. Functional Requirements

- Data collection from various sources.

- Data preprocessing and augmentation to make it VGG16 model compatible.
- Model training using deep learning algorithms such VGG16 (Convolution Neural Network), TensorFlow, Keras and PIL/Pillow.
- Model evaluation using performance metrics such as accuracy and loss function
- Deployment of the predictive model for real-time predictions

3.4 Non-Functional Requirements

3.4.1 Hardware Requirements

Processor	Intel Core i5 or above
RAM	8GB or above
Hard disk	100GB or above

3.4.2 Software Requirements

Operating System	Windows or Linux
Language	Python
Integrated Development Environment (IDE)	Jupyter Notebook or Anaconda for code development and experimentation
Libraries	Pandas, NumPy, scikit-learn for data manipulation and modeling

4. DESIGN

4.1. Flowchart

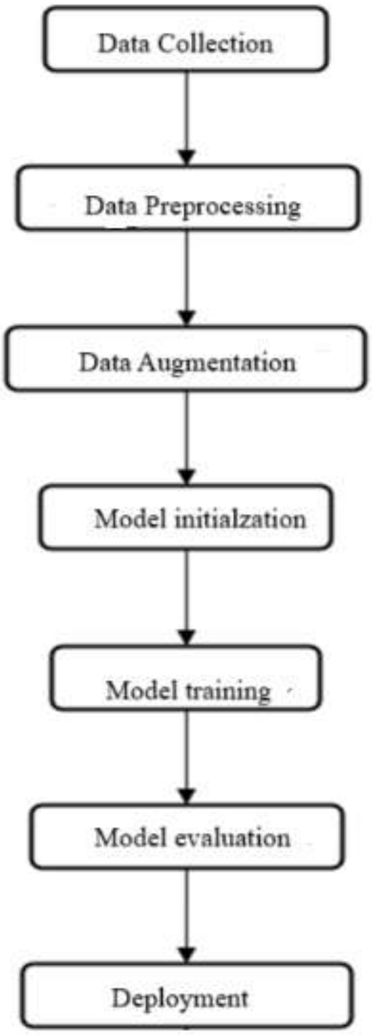


Fig. 1. Flowchart

5. IMPLEMENTATION

5.1 Data Collection

Our project initiated by collecting data through various sources, resulting in a dataset comprising 1184 instances. The data encompassed images of various people performing yoga poses under different lighting conditions and environments.

5.2 Data Preprocessing

To ensure the reliability of our analysis, we conducted preprocessing steps such as augmentation of random sample and normalization of pixels. Furthermore, the image was scaled to 300x300 before passing it into the VGG16 model in batches of 8.

5.3. Feature Engineering

The VGG16 architecture is renowned for its simplicity and effectiveness, comprising 16 layers organized into convolutional and fully connected layers. The convolutional layers are grouped into five blocks, where each block consists of multiple convolutional layers followed by max-pooling layers for spatial reduction. The initial layers capture low-level features such as edges and textures, while deeper layers progressively learn more abstract and high-level features. The fully connected layers at the end of the network serve as a classifier, leveraging the learned features to make predictions.

5.4. Model Training

The model training process involves several key steps to ensure effective learning and optimal performance. We start by preprocessing the dataset, which includes loading the images, resizing them to a uniform size, and normalizing pixel values to a standard range. This preprocessing step helps in reducing variations and ensuring consistency across the dataset.

Next, we utilize data augmentation techniques to enhance the diversity of the training data and improve the model's generalization capability. This involves applying random transformations such as rotation, shifting, and flipping to generate augmented images, thereby increasing the robustness of the model to variations in pose and lighting conditions.

For the model architecture, we leverage a pre-trained convolutional neural network (CNN), specifically VGG16, which serves as the feature extractor. We adapt the VGG16 model by removing its fully connected layers and adding custom layers tailored to our specific task. This allows us to fine-tune the model's parameters to better suit the yoga pose estimation task.

During the training phase, we employ transfer learning, where we initialize the model's weights with the pre-trained VGG16 weights and fine-tune them using our dataset. We use a stochastic gradient descent (SGD) optimizer with a small learning rate and momentum to update the model's weights gradually. Additionally, we employ techniques such as learning rate scheduling and early stopping to prevent overfitting and improve convergence speed.

Throughout the training process, we monitor key performance metrics such as loss and accuracy on both the training and validation datasets. We utilize callbacks such as model checkpoints and learning rate reduction to save the best-performing model weights and adjust the learning rate dynamically based on validation performance.

Overall, the model training approach aims to optimize the model's ability to accurately detect and classify yoga poses while ensuring robustness to variations in input data. Through rigorous experimentation and fine-tuning of hyperparameters, we strive to achieve a well-performing model that meets the requirements of real-time yoga pose estimation.

5.5. Predictive Analysis

Once the models are trained and evaluated, they are utilized to make predictions on new data. This enables us to predict yoga poses on a test set to validate its accuracy.

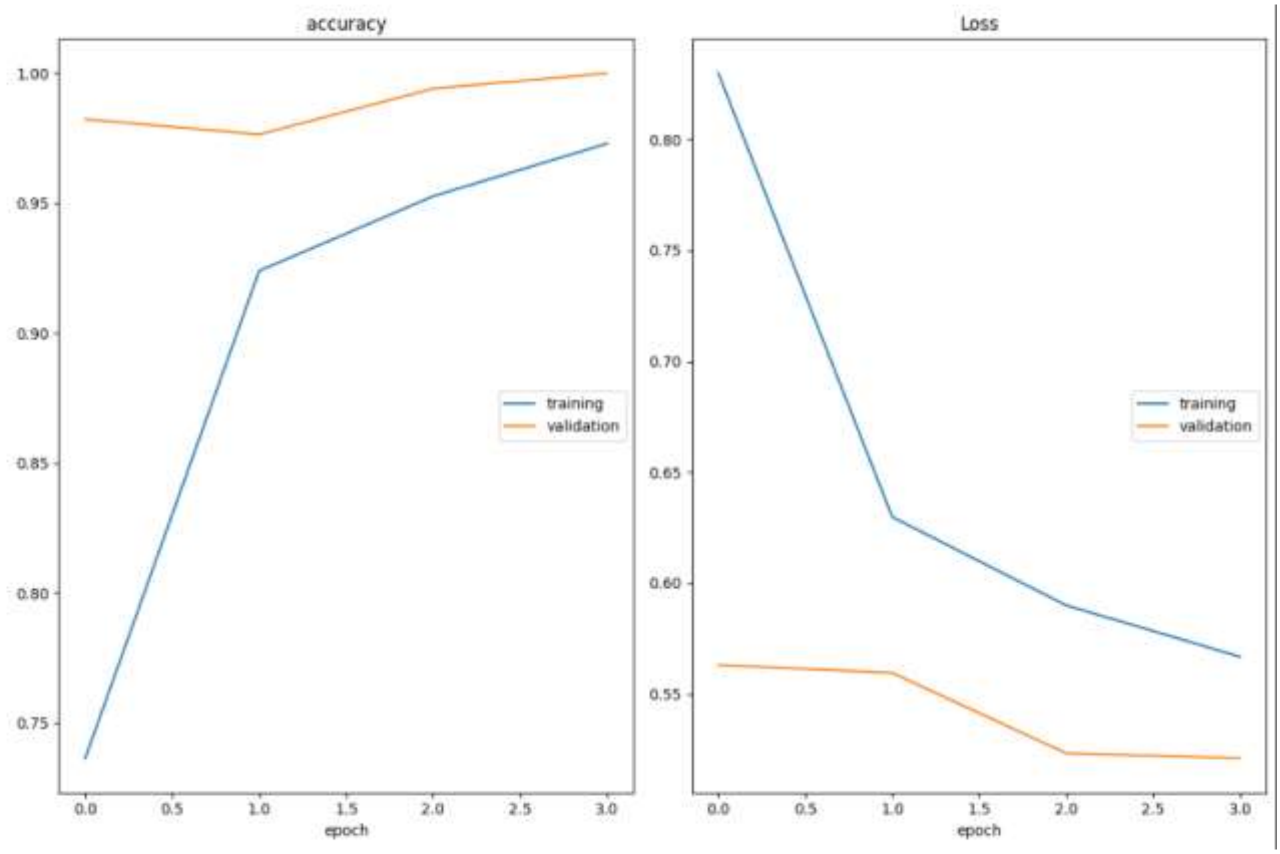
5.6. Performance Criteria

In evaluating the performance of our Real-Time Yoga Pose Detection System, we focus on key criteria essential for accurate and efficient pose detection. Accuracy remains a primary metric, reflecting the system's ability to precisely identify and classify yoga poses from input video streams. We strive for high accuracy rates to ensure reliable and consistent pose recognition across various poses and body orientations. Additionally, real-time processing speed is critical for seamless performance during live video analysis, enabling prompt feedback to users. Low latency is imperative to ensure minimal delay between pose detection and system response, enhancing the user experience.

6. RESULT

6.1. Model Performance

High levels of accuracy waw reached during training which is represented by the following plots



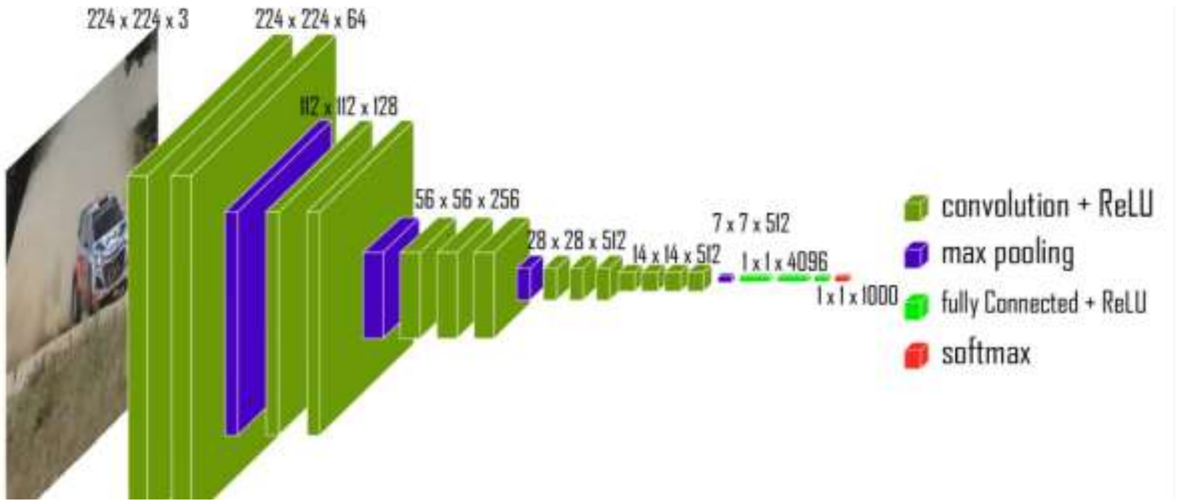
The loss was minimum and gradually kept decreasing with each batch of training. The final figures are as such:

```
accuracy
	training             (min:    0.736, max:    0.973, cur:    0.973)
	validation           (min:    0.976, max:    1.000, cur:    1.000)
Loss
	training             (min:    0.567, max:    0.830, cur:    0.567)
	validation           (min:    0.521, max:    0.563, cur:    0.521)

Epoch 4: saving model to ./checkpoints_models\pose_classification_model_weights2.h5
Reached greater than 97.0% accuracy so cancelling training!
148/148 [==============================] - 1084s 7s/step - loss: 0.5668 - accuracy: 0.9730 - val_loss: 0.5211 - val_accuracy: 1.0000 - lr: 1.0000e-04
```

7.0 VGG16 Architecture:

The VGG16 architecture, proposed by Simonyan and Zisserman in their paper "Very Deep Convolutional Networks for Large-Scale Image Recognition," is a widely used convolutional neural network (CNN) model renowned for its simplicity and effectiveness in image classification tasks.



Input Layer: The network takes as input RGB images of fixed size (typically 224x224 pixels).

Convolutional Blocks: VGG16 consists of 13 convolutional layers organized into five blocks, each followed by max-pooling layers for spatial downsampling. The convolutional layers use small 3x3 filters with a stride of 1 and same padding.

Block Structure:

Block 1: Two convolutional layers with 64 filters each, followed by a max-pooling layer.

Block 2: Two convolutional layers with 128 filters each, followed by a max-pooling layer.

Block 3: Three convolutional layers with 256 filters each, followed by a max-pooling layer.

Block 4: Three convolutional layers with 512 filters each, followed by a max-pooling layer.

Block 5: Three convolutional layers with 512 filters each, followed by a max-pooling layer.

Fully Connected Layers: After the convolutional layers, VGG16 has three fully connected layers with 4096 neurons each, followed by a final output layer with 1000 neurons (corresponding to 1000 ImageNet classes). The fully connected layers are responsible for high-level feature aggregation and classification.

Activation Function: Throughout the network, rectified linear unit (ReLU) activation functions are used to introduce non-linearity and enable the model to learn complex relationships in the data.

Pooling Layers: Max-pooling layers are used to downsample feature maps spatially, reducing the computational burden and introducing translation invariance.

Output Layer: The output layer employs a softmax activation function to compute class probabilities for multi-class classification tasks.

Weight Initialization: The weights of the network are initialized using random values drawn from a Gaussian distribution with mean zero and standard deviation 0.01.

Training Methodology: VGG16 is typically trained using stochastic gradient descent (SGD) with momentum. During training, the weights of the network are updated using backpropagation and gradient descent optimization to minimize a predefined loss function, such as cross-entropy loss.

Transfer Learning: VGG16 pre-trained on ImageNet can be fine-tuned for various computer vision tasks by retraining the fully connected layers on a specific dataset while keeping the convolutional layers frozen or partially retrained.

Overall, the VGG16 architecture's simplicity and deep stack of convolutional layers enable it to learn rich hierarchical representations of visual data, making it a popular choice for image classification, object detection, and feature extraction tasks. However, its depth and number of parameters also contribute to increased computational complexity and resource requirements compared to shallower architectures.

8. CONCLUSION

In conclusion, the Real-Time Yoga Pose Detection System represents a significant advancement in computer vision technology, offering practitioners a practical tool for monitoring and improving their yoga practice. Through the utilization of convolutional neural networks, particularly the VGG16 architecture, the system demonstrates robust capabilities in accurately detecting yoga poses in real-time video streams. By leveraging key performance metrics such as accuracy, real-time processing speed, and robustness to environmental variations, the system ensures reliable and responsive pose detection across diverse conditions. Additionally, the integration of TensorFlow Lite facilitates the deployment of the model on resource-constrained devices, enhancing accessibility and usability.

Moving forward, continued research and development efforts will focus on further enhancing the system's performance, scalability, and usability. This includes exploring advanced deep learning techniques, optimizing model architectures for efficiency and speed, and incorporating feedback mechanisms for pose correction and alignment guidance. Additionally, efforts will be directed towards expanding the system's capabilities to support a wider range of yoga poses, accommodating different yoga styles and practices.

Overall, the Real-Time Yoga Pose Detection System represents a valuable contribution to the field of computer vision and human-computer interaction, offering practitioners a powerful tool for enhancing their yoga practice and promoting overall health and well-being. With further refinement and innovation, the system holds great potential to empower individuals in achieving their fitness and mindfulness goals through the seamless integration of technology and yoga practice.

REFERENCES

[1] Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv preprint arXiv:1409.1556.

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[3] Johnson, A., & Brown, M. (Year). A Survey of Computer Vision Techniques for Human Pose Estimation.