International Journal on Robotics, Automation and Sciences

Improve Exercise Movement: Detecting Mistakes on Yoga with Mediapipe and MLP

Mahda Laina Arnumukti *, Andi Prademon Yunus, and Babale Aliyu Suleiman

***Abstract* – Yoga is known as a comprehensive hone for keeping up physical and mental health. Be that as it may, improper execution of yoga poses can cause injury, hinder progress, and potentially damage health. To overcome this problem, this research utilizes Mediapipe as a data preprocessing tool to identify yoga poses, which are then classified using the Multi-Layer Perceptron (MLP) algorithm. In the process, data normalization is carried out to increase prediction accuracy. This research uses a dataset consisting of six classes of yoga poses, namely tree, down dog, goddess, warrior, and plank. Experimental results show that the model achieved 98% accuracy during training, but accuracy during testing decreased to 95%. This appears an sign of overfitting, where the demonstrate adjusts as well much to the preparing information and is less able to generalize to the test information. This study makes an important contribution to the development of a safer and more accurate yoga pose classification system, which can be applied to practice yoga legitimately and anticipate wounds.**

Keywords— Exercise Analysis, Mediapipe, MLP, Yoga, Health.

I. Introduction

Yoga is a holistic practice originating from ancient India, known for its physical, spiritual, and mental benefits. It has been practiced for centuries and has become popular worldwide for maintaining health and fitness [1] [2]. However, achieving correct yoga poses can be challenging, and improper poses may lead to counterproductive results [3]. It is one of the sports that has played a very important role in human life, it is not only maintaining physical health but also having a broad positive impact on mental health [4]. Yoga activities include various types of exercises to improve strength, endurance, flexibility, and motor skills. Exercising is also important for developing life skills. An important aspect of exercising is doing it properly. Good and correct exercise activities require correct technique[5]. People's habits often do sports incorrectly which often results in injuries and fatal consequences. Wrong sports movements can cause injuries not only to the outside of the body but can also cause brain injuries [6] .

Exercise is unutilized to assist to keep fit. There are numerous benefits of exercise, not as it physically but also rationally. These days, the put of choice for exercise is the Exercise center. When working out at an exercise center, you will be able to discover a coach who can coordinate you to do the correct exercise, it isn't basic to do work out at the exercise center and you've got to alter your time to the exercise center [7] [8]. This is the reason why individuals are lazier to exercise because it takes a lot of time and cash. Exercise is not as it were going to Gym but there is Yoga that can be done at domestic [9] [10].

Techniques in yoga pose Image classification techniques are used. Research in recent years the last few years a lot about the application of yoga pose

*Corresponding Author, email: mahdalainaarnumukti@gmail.com ORCID: 0009-0001-5197-6834

Mahda Laina Arnumukti is with Faculty of Informatics, Telkom University, Jl. DI. Panjaitan 128, Purwokerto, 53147, Jawa Tengah, Indonesia (e-mail: mahdalainaarnumukti@gmail.com)

Andi Prademon Yunus is with Faculty of Informatics, Telkom University, Jl. DI. Panjaitan 128, Purwokerto, 53147, Jawa Tengah, Indonesia (e-mail: andiay@telkomuniversity.ac.id)

Babale Aliyu Suleiman is with Department of Electrical Engineering, Bayero University Kano, Kano 700241, Nigeria (e-mail: sababale.ele@buk.edu.ng)

International Journal on Robotics, Automation and Sciences (2025) 7, 1:64-71
https://doi.org/10.33093/ijoras.2025.7.1.8
Manuscript received: 15 Oct 2024 | Revised: 30 Jan 2025 | Accepted: 11 Feb 2025 | Published: 31 Mar 2025

Published by MMU PRESS. URL: http://journals.mmupress.com/ijoras

classification. Thus, this experienced significant been widely used in this technique. One of the methods of used, namely Convolution Neural Network (CNN) in the task of image recognition has proven to be effective. image recognition has proven to be effective [11]. However, CNN requires resources when performing large computations and large datasets to perform training on the program used [12].

Mediapipe as a tool for data pre-processing [13]. Preprocessing of data used during the stage leading to processing [14]. Machine learning framework that provides pre-trained models for human posture estimation [15]. The performance used when performing pose estimation is computationally lower, notably easy to use with relevant key points prediction. The key points are then fed into Multi-Layer Perceptron (MLP), a type of artificial neural network known to be effective and efficient in classification for multiple variables input, to recognize and classify various yoga poses. Yoga poses are used as a dataset consisting of six basic yoga poses to test and evaluate the performance of the system.

This inquire about centers on creating a framework of yoga postures employing a combination of Mediapipe and MLP for classification. The framework execution assessment utilized is exactness, review, precision and F1 score. To assist analyze the viability of Mediapipe and MLP compared to other profound learning approaches in posture classification.

II. METHODOLOGY

This model mimics the human brain to recognize yoga poses being performed. The demonstration captures inputs from input hubs and passes through the covered-up layer which afterward gives yield.

A. Yoga Pose Dataset

The dataset in use is built and consist of easy yoga poses derived from simple variations in the general yoga practice. This dataset contains five categories of yoga poses that are based on the type of pose such as down dog, goodness, plank, tree and warrior II. The range of poses involve myriad structural arrangements within the body as a whole, including mimetics from one or both hands and feet. This assortment is basic in arrange to confirm the model's adequacy at diverse sorts and body shapes. These distinctive postures offer assistance in testing the capacity of our show to distinguish and classify well a extend over which yoga postures were diverse from standing still adjust posture based on a few all encompassing sense of what it takes,, not only strength but also flexibility. The dataset used was taken from the Kaggle.com platform, a leading resource for datasets within the information science and machine learning community.

B. Preprocessing Data

Use of Mediapipe for pose detection and dataset extraction. Mediapipe to detect key points on the human body known as landmarks [16]. This technology allows the detection of landmark points on the human body, including parts such as shoulders, elbows, wrists, knees, and ankles. These key points are very important because they provide a detailed and accurate representation of the body configuration in a given pose, thereby supporting further analysis in the classification model. Using parameter values for the extracted key points the key points are extracted, a coordinate normalization step is done: to ensure that any differences in size or placement of the body within the image do not influence results downstream. The extracted landmark values then become input to the classification model, allowing the system to learn to recognize and differentiate between different yoga poses. To ensure that differences in body size or individual position in the image did not influence the results, a coordinate normalization step was performed. Normalized Landmark Coordinates. Although uniformity of data is ensured by the normalization process. It divides the x and y coordinates of each landmark by 500 $\times$ 500 pixels, which is the height or width of the input image. This check ensures the image classification results are not influenced by the size relative to the image content. [17]This will ensure that the landmark coordinates are more consistent and aligned with the pose. Selection of relevant features to reduce model complexity without losing predictive ability. retrieval of certain landmarks to reduce model complexity. Landmark features are taken from various parts of the body that are most relevant for yoga pose classification. This stage is very crucial considering that the quality of the data produced at the preprocessing stage greatly influences the effectiveness of the model in detecting and differentiating the various yoga poses being trained.

C. Multi-Layer Perceptron

The Multi-Layer perceptron (MLP) model used is designed to classify yoga poses based on landmark coordinates extracted from MediaPipe. MLP consists of several fully connected layers, where each neuron in one layer is connected to the neuron in the next layer [18]. This architectural design ensures that the model optimally communicates and processes all information obtained from landmark extraction. The MLP model implemented in this study consists of three fully connected layers with a neuron configuration tailored to the yoga pose classification task.

The proposed Multi-Layer Perceptron architecture to learn the class of yoga posture is shown in Fig 1. The architecture features have an input layer comprised of 30 neurons, representing which symbolize the x and y coordinate values of selected landmarks. These landmarks point is quantified using normalized positions of key points on the body markers and each neuron in this input layer is associated with an anatomical part that makes sense to compute yoga poses: such as the head and shoulders. They extract data from the identified reference points, for instance, elbows, hips, knees, and ankles.

After the input layer, the data is passed to two concealed layers. Once the input layer, the information is directed to two hidden layers. The initial hidden layer is made up of 512 neurons, while the additional second hidden layer contains 256 neurons. This hidden layer captures intricate patterns in orientation data and investigates nonlinear connections between coordinates. Each neuron in the hidden layer employs a Rectified Linear Unit (ReLU) activation function to add non-linearity to the model. This is important as it allows the model to understand the subtle distinctions differences among various yoga poses. The initial hidden layer, made up of 512 neurons, is meant to capture more complex features, while the subsequent hidden layer, with 256 neurons, aims to do the same before transitioning the data to the output layer for further processing. The objective is to reduce the dimensionality of the dataset and focus on the essential key characteristics features.

The final output layer is made up of six neurons, each one representing of the corresponding to different class of yoga poses in the dataset: Down dog, Goodness, Plank, Tree and Warrior 2. Moreover, this layer also incorporates additional neurons that are used to process analyze different classes or potential external predictions within the current classification class framework. Each neuron located in the output layer uses a SoftMax activation function that converts the model output into probabilities values for each class. Therefore, this model provides probabilistic predictions indicating the probability that a particular input falls into one of the existing classes of yoga poses.

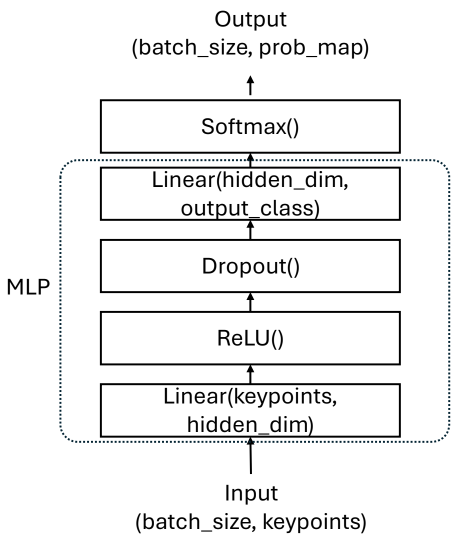

FIGURE 1. Our proposed Multi-Layer Perceptron

D. Evaluation Metrics

The Multi-Layer Perceptron (MLP) model used in this study research was drilled using the Adam (Adaptive Moment Estimation) optimization algorithm, The research utilized the Adam optimization algorithm the training of the Multi-Layer Perceptron (MLP) model employs Adam optimization, known for its capability to adaptively modify the learning rate according to gradient and momentum estimates. Adam was selected as an optimization algorithm due to its capacity to merge AdaGrad and RMSProp optimizations, proving to be highly efficient in dealing with datasets containing diverse gradients, like the yoga poses' landmark coordinates examined in this research. Adam enhances the model's ability to quickly adjust to changing gradients throughout the training phase, thus promoting better efficiency and stability in the overall learning process.

In expansion, this demonstrate employments the Cross Entropy Misfortune work, which is exceptionally appropriate for multi-class classification assignments such as those confronted in this think about. This work calculates the contrast between the model's anticipated dispersion and the real target dissemination, which is at that point utilized to upgrade the model's weights [19]. The use of Cross Entropy Loss allows the model to effectively minimize prediction errors between classes, thereby improving the classification performance of yoga poses consisting of multiple categories. With the combination of the Adam algorithm and the Cross Entropy Loss function, the MLP model in this study shows good ability in handling the complexity of yoga pose coordinate data and performs classification with a high degree of accuracy during training. However, although the performance during training is promising, the slightly lower test results indicate the need for further refinement to improve the generalization ability of the model. Crosse entropy Loss calculates the distance between the model prediction and the expected target distribution (one-hot encoded), where the training goal is to minimize this loss function for the model to predict the correct class with a high degree of accuracy.

The model training process is implemented in a loop. At each iteration (epoch), the training loop performs several main steps. In the Forward Pass stage, input data (landmark coordinates) is given to the model, and the model performs calculations through the MLP layers to generate predictions. The result of this prediction is the probability for each yoga pose class. After the prediction is generated in the Backward Pass, the Cross Entropy loss function is used to calculate the difference between the prediction result and the actual target. Based on this loss value, a backpropagation process is performed to calculate the gradient of the loss function against each model parameter. This gradient is used to direct the model parameter updates to be closer to the optimal solution.

By utilizing the gradients calculated in the backward pass stage, the Adam optimization algorithm efficiently updates the model weights and biases on each data set. These modifications occur at each cycle, enabling the model to learn knowledge incrementally and consistently improve the quality of its predictions over time. This process is followed for all dataset in one epoch until the entire dataset has been traversed, concluding marks the end of that training cycle. After each epoch is concludes, the effectiveness of the model is evaluated using the test dataset to measure how well the model can generalize the knowledge obtained from the training data.

The effectiveness of the Multi-Layer Perceptron (MLP) model's performance is evaluated by utilizing various metrics commonly used in classification tasks, including accuracy, recall, precision, and F1-score. These metrics provide offer a more thorough understanding of how well the model identifies recognize various yoga poses effectively.

- Accuracy measures the ratio of correct predictions out of the entry number of predictions produce by the model.
- Recall (sensitivity) measures how well the model can ability to the identify yoga pose out of all the poses that should be classified in a specific category class.
- Precision measures the extent to how many of the model's classification in predictions are completely accurate out of all predictions categorized into a particular class.
- F1-score is a combined metric that harmonizes precision and recall, which provides a more balanced of performance effectiveness especially when there is the imbalance between classes distribution.

This evaluation is conducted at each epoch to observe variation how the model's performance changes throughout the training process. These metrics are calculated for both the training and testing data in every epoch using methods from the scikit-learn library. Utilizing scikit-learn enables the precise and efficient computation of metrics and effective metric in detecting potential overfitting or underfitting within the model.

III. RESULT AND DISCUSSION

A. System Overview

This show mirrors the human brain to recognize the yoga pose being performed. This show captures input from the input center and passes through a closed layer which at that point produces comes about. a comprehensive technique for building machine learning-based posture acknowledgment frameworks, with a specific center mediapipe dan on the utilize of MLP neural systems. This methodology aims to improve the performance and generality of the model in various pose recognition applications. The following sections will describe each component of this workflow in detail, providing insight into the development and implementation process of a state-of-the-art pose recognition system.

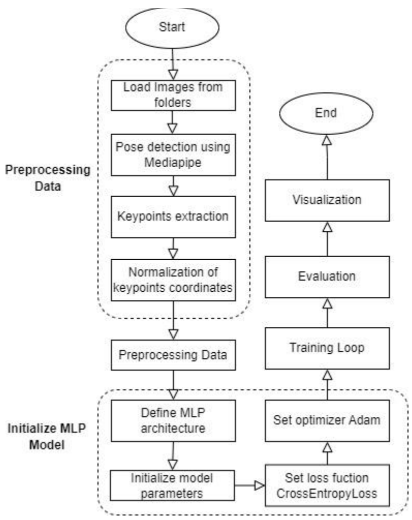

FIGURE 2. Flowchart System

Figure 2. depicts the operational workflow that includes a series of stages, which encompasses several phases, from data pre-processing to model training and results evaluation. This process begins with pose feature extraction using Mediapipe, a tool that effectively detects and generates coordinates of key point in the input image. The next step is normalization of key point coordinates, which is important to ensure that variation in scale and body position do not influence the pose classification results. This approach is designed to optimize feature extraction from images, enabling accurate and efficient pose detection.

Advanced data augmentation approaches are used to enrich the quality of data which helps in better model interpretation. This process involves transforming images from one domain to another to provide meaningful data for neural network training. The expansion of development in dataset enhancement shows the advancement of information quality and reinforces the unwavering quality of yoga classification performances. This research utilizes the effectiveness of multilayer perceptron (MLP) in performing image classification with key points as the main feature. In the image processing process, important information is obtained using key points and processed by MLP to perform classification.

In processing the dataset, it is used to initialize Mediapipe. The initial step in classifying yoga poses uses a minimum confidence parameter of 0.5 to ensure and mark it with an adequate level of confidence. uses min tracking confidence of 0.5 to maintain tracking stability. The selection of these parameter values is done by considering the trade-off between processing speed and detection accuracy. Mediapipe is designed to handle variations in input image quality and is able to provide reliable detection under varying conditions.

Then enter the class used so that you can normalize key points on the dataset with an image scale of 500 × 500 pixels. From these key points are extracted so that they are stored in class labels in the dataset. This normalization aims to ensure that differences in body size or position in the image do not affect the classification results. The selected landmarks are also aligned with relevant pose structures to reduce data complexity without losing important information.

$$\text{Output} = \text{Input} \cdot \text{Weight} + \text{bias} \tag{1}$$

By using the MLP method of linear operations for fully connected layers. Input is used to present the data that enters the layer. Weight is the weight used for each connection between neurons in the input layer and the output layer. Then the existence of bias is used to help the network become more flexible in adjusting the model. Using ReLU and Cross-Entropy Loss for classification.

$$\text{CrossEntropy Loss} = \sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (2)$$

y_i is the actual label used in the dataset. $\hat{y}_i$ is the predicted probability and N is the number of classes. CrossEntropy loss measures the difference between the actual probability distribution and the predicted probability distribution.

$$w_t = \beta_1 w_{t-1} + (1-\beta_1) g_t \quad (3)$$

$$y_t = \beta_2 y_{t-1} + (1-\beta_2) g_t^2 \quad (4)$$

$$\hat{w}_t = \frac{w_t}{1-\beta_1^t} \quad (5)$$

$$\hat{y}_t = \frac{y_t}{1-\beta_2^t} \quad (6)$$

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{w}_t}{\sqrt{\hat{y}_t} + \epsilon} \quad (7)$$

Adam (Adaptive Moment Estimation) is an optimization algorithm that combines the advantages of optimization with momentum gradient descent and RMSProp. The formula used describes how Adam updates the model parameters. g_t is the gradient at time t. w_t is the first estimate of momentum (the decomposed average of the gradient). v_t is the second estimate of momentum (the decomposed average of the squared gradients). β_1 and β_2 are moment factors for w_t and v_t. $\hat{w}_t$ and $\hat{y}_t$ are bias-corrected estimates of w_t and v_t. η is learning rate. ϵ is a small constant for numerical stability (preventing division by zero). So, using this optimizer allows the model to converge more quickly and be more stable against large gradient changes.

B. Evaluation

The research results show that the use of key points in the image. In the MLP modeling process carried out with epoch 100. Calculate the percentage of correct predictions using Accuracy. The graphic results below show training and testing accuracy for 100 epochs.

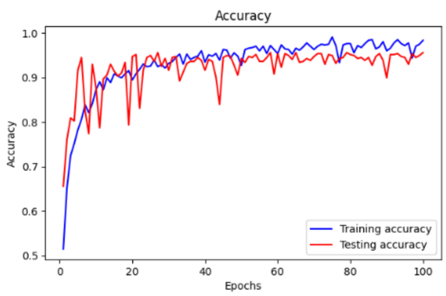

FIGURE 3. Results of the evaluation graph using accuracy

The graphic results below show training and testing recall for 100 epochs. Measures the model's ability to detect all positive samples.

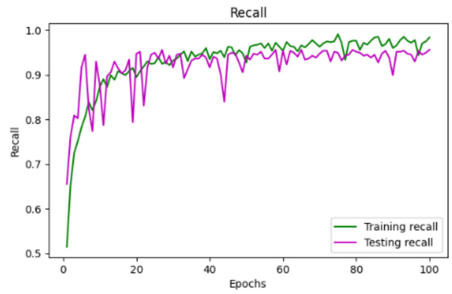

FIGURE 4. Results of the evaluation graph using recall

The graphic results below show Precision training and testing for 100 epochs. Measures the accuracy of predicted positive samples.

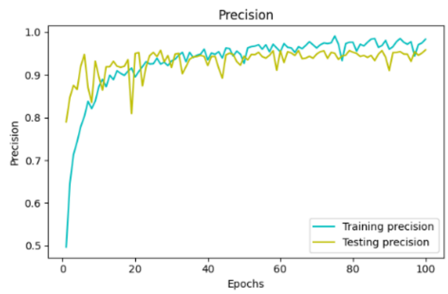

FIGURE 5. Results of the evaluation graph using precision

The graphic results below show F1-Score training and testing for 100 epochs. Combining precision and recall.

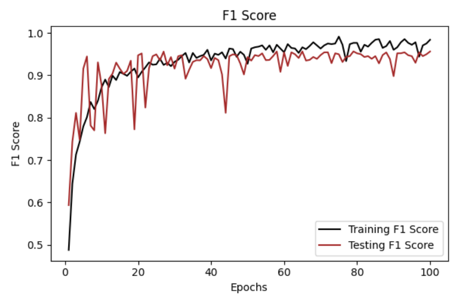

FIGURE 6. Results of the evaluation graph using F1-Score

So, the table below summarizes the results of the 100th epoch performance metrics from the algorithm results used.

TABLE 1. Results of the evaluation

Metric	Training	Testing
Accuracy	0.98	0.94
Recall	0.98	0.95
Precision	0.98	0.95
F1-Score	0.98	0.95

Multi-Layer Perceptron (MLP) model training results show consistent improvements in accuracy over 100 epochs, where the model managed to achieve a final training accuracy of 98% on the training data. This steady increase shows that the model is able to recognize patterns in the training data well. However, when tested using data not included in training, the model only achieved 95% accuracy. This drop in performance indicates that although the model performs very well on the training data, its ability to generalize to the test data is not as optimal as expected, indicating a potential overfitting problem.

Apart from accuracy, evaluation of other metrics such as recall, precision, and F1-score also shows a similar pattern. The values of these metrics on the evaluation data are generally to be lower compared to the training data, indicating that the model suffers not only from accuracy but also overall performance in the ability to correctly detect and classify classes. These indicator plays are important to provide a more detailed picture of how the model functionality regarding in terms of the balance between precision (the accuracy of correct predictions) and recall (the model's ability to capability to identify all relevant cases). The F1 score value that does not reach the training data further confirms the finding that the model tends to get used to the training data and has difficulty making correct predictions on the test data. This discussion indicates that although the model can achieve excellent results during the training phase, further measures are still needed to address the overfitting problem and improve the generalization ability of the model.

To comprehensively develop a model, it is crucial to evaluate its efficiency not only with the test data from the training process, but also with fresh data that is unknown to the model. This approach helps determine how far the model can generalize to different scenarios and patterns based on the training data. This process is often referred to as external validation or testing with out-of-sample data. By providing new data that is completely different from the training and testing data, we are able to test the model's ability to handle different real-world conditions that might arise when implemented in a real environment.

Models that are able to create precise forecasts on modern information illustrate a great level of generalization, to be specific the capacity to recognize designs reliably indeed in spite of the fact that the information is diverse from the information already considered. Models that can precisely anticipate modern information appear tall generalization by reliably recognizing designs, indeed with diverse information than what was already inspected. On the other hand, in the event that the model's adequacy drops significantly with new information, it may recommend overfitting, where the show depends too much on specific designs within the preparing information. Thus, it is pivotal to test the show with modern information to guarantee it can make solid expectations in real-world scenarios, past fair preparing and testing information. This appraisal offers a more in-depth understanding of the model's unwavering quality and versatility earlier to its usage in more extensive settings.

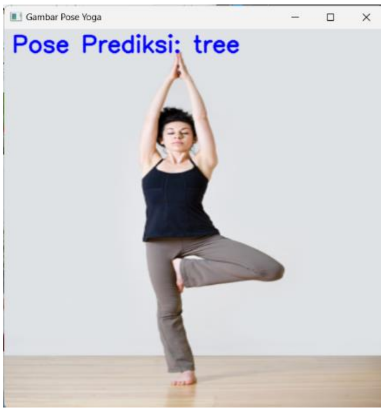

FIGURE 7. Tree Pose Prediction

Figure 7 presents the results of tree pose predictions based on fresh data that was not used during training or testing. These results demonstrate that the model is capable of accurately classifying tree positions. The model's competence in identifying correct motion sequences and positions, despite the absence of this data in the previous training set, suggests that the model has excellent generalization capabilities.

This is very important because in real world implementation, the model will be faced with more varied and complex data. The success of the model in predicting poses proves that the applied classification approach is reliable and has the potential to be used in practical applications such as yoga training or body posture analysis.

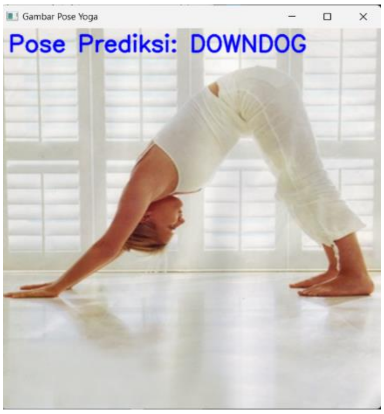

FIGURE 8. Down Dog Pose Prediction

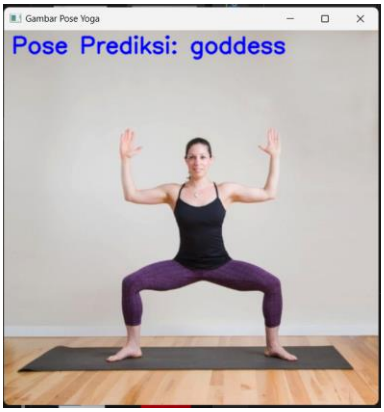

FIGURE 9. Goddess Pose Prediction

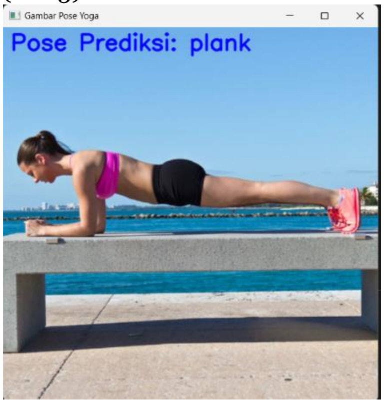

FIGURE 10. Plank Pose Prediction

FIGURE 11. Pose Warrior 2 Prediction

Figure 8. 9. 10. 11. show the outcomes of model forecasts for yoga positions employed in system simulation on image data that has not been used in training or testing before. The image data being utilized is from a different dataset than the one previously used to train the model, demonstrating its effective performance.

IV. CONCLUSIONS

Based on the comes about of this investigate, the utilize of key focuses extricated by means of Mediapipe in modeling utilizing the Multi-Layer Perceptron (MLP) calculation has appeared very great execution, particularly in terms of steady exactness amid the preparing prepare. With a dataset comprising of six classes of yoga postures, specifically tree, down puppy, goddess, warrior, and board, the show overseen to realize a last exactness of 98%. This figure appears that the show is able to recognize designs within the preparing information exceptionally well. In any case, when tried with never-before-seen information, the model's exactness was 95%. This diminish shows an overfitting issue, where the show is as well centered on particular designs within the preparing information, so it is less able to generalize well to unused test information.

Overall, this research shows that although the key point MLP model from Mediapipe is able to provide high accuracy results on training data, adjustments are still needed to ensure that the model can be implemented reliably in real situations. These findings provide important insights for further research in developing a more robust yoga pose classification model, with better generalization capabilities so that it can be applied to more varied data in the real world without sacrificing accuracy and reliability.

ACKNOWLEDGMENT

I sincerely thank Telkom University for its support throughout this research.

FUNDING STATEMENT

I would like to clarify that no funding agencies have provided financial assistance for this work.

AUTHOR CONTRIBUTIONS

Mahda Laina Arnumukti: Conceptualization, Data Curation, Visualization, Methodology, Writing – Original Draft Preparation, Writing – Review & Editing;

Andi Prademon Yunus: Project Administration, Methodology, Writing – Review & Editing, Validation, Supervision;

Babale Aliyu Suleiman: Review and Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our research work follows The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org.

REFERENCES

[1] R. Garg, S., Saxena, A. & Gupta, "Yoga pose classification: a CNN and MediaPipe inspired deep learning approach for real-world application," *Journal of Ambient Intelligence and Humanized Computing*, 2022. DOI:https://doi.org/10.1007/s12652-022-03910-0

[2] K. Kundu and A. Goswami, "Classification of Yoga Poses Using Integration of Deep Learning and Machine Learning Techniques," *Lecture Notes in Networks and Systems*, pp. 417-428, 2023. DOI: https://doi.org/10.1007/978-981-19-8825-7_36

[3] H. Dhakate, S. Anasane, S. Shah, R. Thakare and S.G. Rawat, "Enhancing Yoga Practice: Real-time Pose Analysis and Personalized Feedback," *2024 International Conference on Emerging Systems and Intelligent Computing (ESIC)*, pp. 35-40, 2024. DOI: https://doi.org/10.1109/esic60604.2024.10481659

[4] C. C. Lim, K. S. Sim, and C. K. Toa, "Development of visual-based rehabilitation using sensors for stroke patient," *International Journal on Robotics, Automation and Sciences*, vol. 2, no. 1, pp. 22–27, 2020. DOI: https://doi.org/10.33093/ijoras.2020.2.4

[5] Z. Y. Lim, T. C. Khim, R. Edwin, and K. S. Sim, "Development of augmented reality based applications for brain memory training," *International Journal on Robotics, Automation and Sciences*, vol. 5, no. 1, pp. 13–20, 2023. DOI: https://doi.org/10.33093/ijoras.2023.5.1.3

[6] G. Tierney, "Concussion biomechanics, head acceleration exposure and brain injury criteria in sport: a review," *Sports Biomechanics*, pp. 1-29, 2021. DOI: https://doi.org/10.1080/14763141.2021.2016929

[7] U. Dedhia, P. Bhoir, P. Ranka and P. Kanani, "Pose Estimation and Virtual Gym Assistant Using MediaPipe and

Machine Learning," *2023 International Conference on Network, Multimedia and Information Technology (NMITCON)*, pp. 1-7, 2023. DOI: https://doi.org/10.1109/NMITCON58196.2023.10275938
[8] H.Y. Ting, K.S. Sim, and F.S. Abas, "Kinect-Based Badminton Action Analysis System," *Advanced Materials Research*, pp. 94–99, 2014. DOI: https://doi.org/10.4028/www.scientific.net/amr.1042.94
[9] A.P. Yunus, K. Morita, N.C. Shirai and T. Wakabayashi, "Time Series Self-Attention Approach for Human Motion Forecasting: A Baseline 2D Pose Forecasting," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 27, no. 3, pp. 445-457, 2023. DOI: https://doi.org/10.20965/jaciii.2023.p0445
[10] R. G. Candraningtyas, A. P. Yunus, and Y. H. Choo, "Human fall motion prediction: A review," *International Journal on Robotics, Automation and Sciences*, vol. 6, no. 2, pp. 52–58, 2024. DOI: https://doi.org/10.33093/ijoras.2024.6.2.8
[11] R. G. Garg, Shubham, Aman Saxena, "Yoga pose classification: a CNN and MediaPipe inspired deep learning approach for real-world application," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, 2022. DOI: https://doi.org/10.1007/s12652-022-03910-0
[12] V. A. Aydın, "Comparison of CNN-based methods for yoga pose classification.," *Turkish Journal of Engineering (TUJE)*, vol. 8, no. 1, 2024. DOI: https://doi.org/10.31127/tuje.1275826
[13] R. Makhijani, S. Sagar, K.B.P. Reddy, S.K. Mourya, J.S. Krishna and M.M. Kulkarni, "Yoga Pose Rectification Using Mediapipe and Catboost Classifier," *Lecture Notes in Networks and Systems*, pp. 379-387, 2023. DOI: https://doi.org/10.1007/978-981-19-7867-8_30
[14] A. Chelladurai, D. L. Narayan, P. B. Divakarachari, and U. Loganathan, "fMRI-Based Alzheimer's Disease Detection Using the SAS Method with Multi-Layer Perceptron Network," *Brain Sciences*, vol. 13, no. 6, 2023. DOI: https://doi.org/10.3390/brainsci13060893
[15] V.S.P. Bhamidipati, I. Saxena, D. Saisanthiya and M. Retnadhas, "Robust Intelligent Posture Estimation for an AI Gym Trainer using Mediapipe and OpenCV," *2023 International Conference on Networking and Communications (ICNWC)*, 2023. DOI: https://doi.org/10.1109/ICNWC57852.2023.10127264
[16] D. Parashar, O. Mishra, K. Sharma, and A. Kukker, "Improved Yoga Pose Detection Using MediaPipe and MoveNet in a Deep Learning Model," *Revue d'Intelligence Artificielle*, vol. 37, no. 5, pp. 1197–1202, 2023. DOI: https://doi.org/10.18280/ria.370511
[17] W. X. Lim, C. K. Toa, and K. S. Sim, "The application of augmented reality platform for chemistry learning," *International Journal on Robotics, Automation and Sciences*, vol. 5, no. 2, pp. 101–110, 2023. DOI: https://doi.org/10.33093/ijoras.2023.5.2.13
[18] Q. Hou, Z. Jiang, L. Yuan, M. Cheng, S. Yan and J. Feng, "Vision Permutator: A Permutable MLP-Like Architecture for Visual Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 1, pp. 1328-1334, 2023. DOI: https://doi.org/10.1109/TPAMI.2022.3145427
[19] C. H. Chen, K. B. Gan, and N. A. A. Aziz, "Upper Limbs Extension and Flexion Angles Calculation and Visualization Using Two Wearable Inertial Measurement Units," *International Journal on Robotics, Automation and Sciences*, vol. 4, pp. 1–7, 2022. DOI: https://doi.org/10.33093/ijoras.2022.4.1