AI-Driven Personalized Fitness Coaching with Body Type-Based Workout and Nutrition Plans and Real-Time Exercise Feedback

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Abstract: ***In today's fast-paced world filled with distractions such as work, family, education and other commitments, people often have little time and energy to maintain a healthy lifestyle. Traditional fitness approaches frequently fail to meet the dynamic needs and expectations of modern users, leading to dissatisfaction and disengagement. A main problem of traditional systems is the lack of personalization for diverse users, that also monitors and tracks the workout progression. This study introduces an innovative system that creates a personalized workout and diet plan which aims to engage and motivate the user experience by individual personalization. Through means such as real-time exercise tracking and feedback mechanisms, this mobile fitness application aims to address limitations of traditional fitness approaches, proving fitness experience for users to achieve their health and fitness goals in a convenient and sustainable manner***

Keywords: CNN, YOLOv8, Body Type Identification, Personalized Workout Plans, Real-Time Feedback, Personalized Dietary Recommendations, Image-Processing, Random Forrest Classifier Machine Learning.

I. INTRODUCTION

Advancements in fitness related technology have revolutionized how individuals approach health and wellness [1]. The fitness-related coaching and dietary planning system represents significant advancement in personalized fitness and nutrition [2]. With the widespread use of technology, having mobile applications is also part of our life nowadays. Many people frequently use mobile applications for most activities. Currently, there are lots of nutrition/fitness applications that are mobile based and web-based, that provide recommendations for users supporting to achieve their fitness goals. Most fitness applications in use today are used to collect biometric parameters like heart rate, speed and other relevant data using wearable devices [1]. Generic fitness applications do not consider the wide variety of body types and fitness levels of their users, which is a significant limitation.

Nowadays it is more difficult to concentrate on health and fitness because of a busy lifestyle. Finding a knowledgeable and affordable physical trainer can be difficult. As a result, many individuals are in a difficult situation, using generic mobile applications or overpaying for physical coaching [3]. The lack of customization and real time fitness activities in traditional fitness applications can be a major setback as many generic fitness applications do not cater to the varied needs and preferences of individuals, providing standardized solutions may not be suitable for all users [4]. Some of the current applications offer general workouts and nutrition advice that do not consider the differences, such as body types, the level of physical fitness and how these impact people individually are generally ignored in their design [5]. These applications fail to consider the significance of addressing the different body types and composition in the workout plan and dietary plan creation. These body types have distinct physiological traits that affect how individuals react to exercise and diet. Another major problem for today's fitness lovers is dealing with the absence of personalized assistance and guidance. Furthermore, the problem is made worse by the fact that current fitness applications lack real-time feedback features. Incorrect performance of exercises may create a high risk of physical injury. Insufficient intake of essential nutrients can lead to muscle and bone weakness, rendering them more vulnerable to exercise-related injuries [6]. Current methods are generally not flexible enough to combine dietary recommendations with other aspects of lifestyle. Traditional methods of dietary recommendations are inefficient.

This research proposes a comprehensive solution for users to achieve their fitness goals efficiently using modern technologies including image processing, computer vision and machine learning. Firstly, the system identifies the user's body type and will categorize the user into a specific somatotype. Furthermore, the system will provide the user with a

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workout plan and dietary plan to follow which can be adjusted according to user preferences. A timeline is generated for the user to estimate the time taken to achieve their body goal. When the user follows the generated workout plan, the performed exercises are monitored by the system in real time and in the case of an incorrect performance of an exercise, a notification is given a real-time and the movement is corrected. The system is set according to industry standards in fitness and performance for user satisfaction.

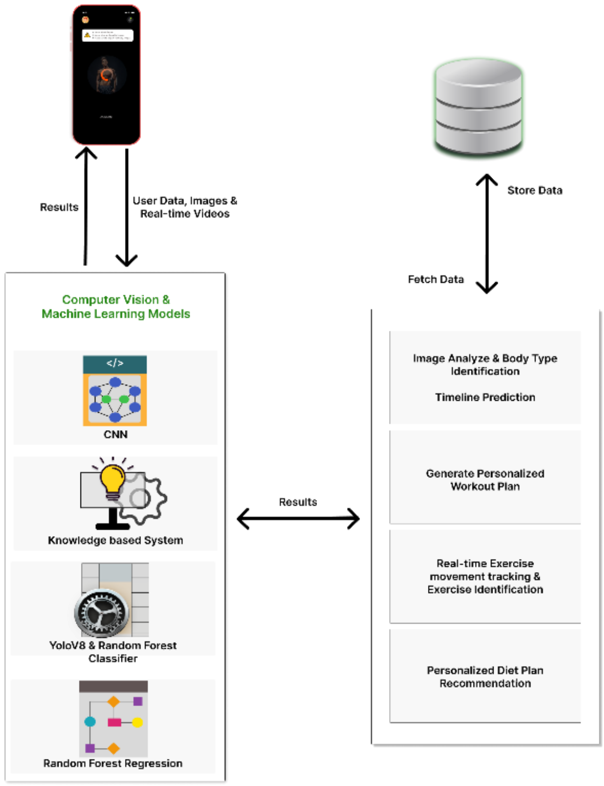
II. LITERATURE REVIEW

Matthias Kranz et al [7]. developed a system based on assessing the individual skill of a user, using personalized mobile devices. By leveraging built-in sensors to support physical training through detailed exercise descriptions, data logging, and skill assessment. In the proposed system which is the "FIT GENIUS" mobile application an avatar was developed to display the correct performance of exercises and display exercise related data for additional user-friendliness.

Santhiramohan Madhushika et al [8]. "SMART"- "Machine Learning Based Fitness Mobile Application "is a paper that develops a mobile based application that is based on machine learning and image processing to enhance user fitness experiences. The application, called SMART, aims to provide a solution to attain the user's health and fitness goals by enhancing their fitness experience by providing personalized workout routines, dietary suggestions, and equipment recommendations, all tailored to the user's requirements. The paper highlights the app's ability to function as a virtual personal trainer for the user. The way this system differs from the "Fit genius" mobile application is the higher level of personalization that the fit genius mobile application provides to the user also giving a wider variety of customizable workout plans and most importantly the identification and correction of exercise movements giving real time feedback to the user. The Harris-Benedict equation, which is among the oldest estimates for BMR, involves weight, height, age as well as gender to find out how much energy a person uses while at rest. This approach has been tested on different populations after it was discovered by subsequent research Harris et al [9]. The current study uses sex-linked equations based on men's and women's varying body compositions and metabolic rates to make more precise estimations. Choudhary et al [10]. developed an application to measure the waist-to-hip ratio (WHR), which is a measurement that compares the circumference of the waist to that of the hips, it is calculated by dividing the waist measurement by the hip measurement. A problem developed by this method is the over emphasis and focus on abdominal body fat, having a limited scope of measurement in the analysis of user body type. In this research additional body measurements such as (BMI) provide a more accurate assessment of body composition.

On analyzing the research by Tóth et al [11]. was a similar study on the somatotypes in athletes who are participating in various sports. The research focused on identifying the suitable body types for specific athletic activities. One major drawback of this method is the fact that the data is largely based on athletes, making it difficult to apply to the average user. A wider range of focus is crucial to analyze users having very diverse and unique body types therefore this research has taken a wide range of users to train machine learning models. Considering fitness systems such as Pulasinghe et al [12]. developed focused on using object detection algorithms such as (WHR) which is not adequate at classifying complex body types. This study used a MobileNetv2 based CNN model with specifically trained and labelled dataset for diverse body type recognition which addressed this problem. Furthermore, personalized workout plan systems such as FitRec model used static criteria, for example gender, weight, and activity levels but it has been shown that dynamically based systems are more effective in user retention and user contentment. This research uses a personalization algorithm that evolves exercise plans according to user preference and goals. The tracking system in Pulasinghe et [12] al. functions as a simple movement tracker while this study uses a high precision tracker and a real time corrective feedback system. The dietary system in Pulasinghe et al [12]. used generalized data inputs and fixed calory count was used. Making the output linear and simple, A random Forrest regressor was employed with linear programming in this study to produce adaptive meal plans that showed user specificity and adaptability which allowed for dynamic growth.

III. METHODOLOGY



[Fig.1: Overall System Diagram of the Proposed Solution]

As shown in the figure above, registered users will upload a body image as instructed and guided by the system. The images are sent to the Amazon Web Services (AWS) backend server where the fast API is deployed using the CNN model in the backend server to identify the body type. Then through the API endpoint the identified body type is sent to the mobile app. Then the user inputs their height, weight, and end body goal, based on the body type and the other gathered data a workout plan is given. According to the user feedback the exercises regiments can be varied dynamically using the knowledge-based system. Also, a timeline in which the users desired end goal can be achieved is shown on the user profile. To make sure the user performs the exercise correctly a real-time exercise movement tracking system is used where the user performs the exercise Infront of a mobile phone and the real time captured video footage is transmitted to the (AWS) backend, and the WebRTC is deployed where the video is streamed and processed , Here the random Forrest classifier model identifies if the correct exercise is performed by the user while the YOLOv8 detects if the exercise movement performed by the user is also correct. A diet plan is given to the user considering factors such as height, weight, BMI, weekly exercise duration, user preferences and the user's end goal. A daily calory limit is calculated according to the above data. The user's preferences, exercise duration and other data are taken using a thorough questionnaire, a random Forrest regressor model and linear programming is used to personalize it according to the user preferences and multiple dietary plans are given for the user's selection.

A. Identify the Human Body type Using Image Processing

A comprehensive dataset of human body images was used to understand and categorize body types. This collection has 3 main body types that were categorized as ectomorph, endomorph, and mesomorph. These 3 main body types are included for both men and women. It also includes images of individuals with a variety of physical buildings including from slender to well-built figures. The data sets quality and depth have been constructed by the application of rigorous preprocessing techniques. These steps include resizing where the image dimensions were standardized to ensure uniformity throughout the dataset. Normalization, in which the pixel values were adjusted to a common scale which helps in the improvement of image analysis algorithms and Augmentation, where transformations like rotation, flipping and scaling were used to enhance the datasets diversity and robustness. Each image was carefully sorted and labelled according to the appropriate body type and gender, and this information was organized in a structured manner, such as a csv file. Then the organized dataset is used for the training and validation of the machine learning models.

The trained model within the dataset uses a Convolutional Neural Network (CNN) algorithm to classify the body type effectively. The first step is Data splitting where the dataset was split 80% for training and 20% for testing, thus ensuring that the model is properly trained so the model can later be trained against unseen data. In the Augmentation of Data methods such as rotation flipping and scaling are used to transform data so that many variations exist in the training set. Data overfitting is prevented by using this method. In Model architecture a pre-trained model of MobileNetv2 is used as the base model for the CNN model, it is the most efficient and accurate model forclassification problems in image recognition. Custom Layers: Several layers were added to the model prepared over the base model for the CNN model, The layers include the global Average pooling layer, Batch Normalization layer, Dropout layer and dense layer. In model compilation, the model was compiled using an Adam optimizer and categorical cross-entropy loss function, this is well suited for multi-class classification problems. Finally in training, the model was trained using the training dataset with a batch size of 32 and a learning rate of 0.0001. Several types of callbacks such as early stopping, model checkpoint, and Reduce LR On Plateau were used in facilitating the training process also to regularize the model. Also, using trained a Random Forest regressor model, the timeline in which the user can attain their body goal was identified. Once the training process of the machine learning model is completed it will mainly complete three functions. Firstly, identification of the user body type as either mesomorph ectomorph or endomorph using the trained model then the user will be given a selection option, the options for the user to select will depend on the user's identified body type. The user can choose whether to gain or lose weight according to their preference. Using body type data and the goal user selected the time taken to achievement of the user's goal is predicted.

B. Generate Personalized Workout Plans

Firstly, in data collection, the creation of a workout plan requires a good knowledge base for the system to be built. Data collection is thus an important aspect of this development with the aim of achieving a comprehensive list of workouts. There are several sources of data that may be present in this work such as user surveys, recognized sites dealing with matters of fitness, and certified personal trainers. Data collected from the above sources was used in the creation of the set of exercises to address different user fitness goals. In Data Classification, the gathered data in exercise classification comprises the subsequent process. Every exercise is classified based on several criteria like the type-strength, cardio, or yoga; the primary goal targeted-strength, endurance, flexibility, and a few other details like the total number of sets, repetitions, time, etc., week level for progression. Personalization Algorithm - It forms the backbone of the knowledge base system. The algorithm's design is such that it has the plan of a workout personalized on preference, level of fitness and goal determination. Validation goes into the kind of data used and falls within classes. The algorithm designs plan, therefore, on the specific needs of the user, hence giving effective clues with engaging exercises. The workout plan needs to be fine-tuned and polished; for that, a mechanism for incorporating user's' feedback is necessary. In the app, there is an emoji-based feedback system by which the user can mark his satisfaction with each exercise in a very convenient way. The feedback is stored and analyzed to recognize the trend of preferences of the users and to make out the scope for improvement.

C. Exercise Movement Tracking System with Real-Time Feedback

The first step was to capture the exercises performed correctly and accurately by a professional and qualified gym instructor. In this was the
initial dataset that can be created which serves as the foundation and the corrective guide for every exercise performed by the user. High quality cameras and multiple angles were used to record the exercises performed by the instructor. The recordings were taken of the highest quality possible as they will serve as the foundation for training the system's algorithms. The captured video footage is then subjected to further preprocessing using the YOLO model8, the video data that has been captured will be refined and is focused on the correct exercises, movements and poses. After the process, the processed video data is converted to a dataset of coordinates using OpenCV and Media pipe. The coordinates for the landmarks are taken using the x and y axis points. For each frame of the exercise video the coordinates are taken and saved into the dataset, for each body-land-mark a coordinate is taken from the horizontal (x axis) and the vertical (y axis) by media pipe, from the edge of the frame to that specific body-landmark. Yolo identified the center of the person and the edge of the frame then the two distances from the two horizontal and vertical edges are saved as the coordinates for each landmark. This is done to begin the computational analysis of the captured exercise data. In this each co-ordinate is labelled according to the exercises that are being performed therefore an organized and searchable data set can now be created.

The collected dataset of videos was divided into training and testing sets, with 80% of the videos used for training and the remaining 20% for testing. This division ensured that the model was trained on a substantial amount of data while having a separate set for evaluating its performance. In such manner the training and testing split is optimized to enhance the learning process. Now using the created dataset, a random forest classifier model is trained. This model is used to identify each of the exercises performed by the user. The developed computer vision algorithm using yolo and media pipe body coordinates. Yolo identifies the person which is a pre-processed by the yolo model. Media pipe is used to identify the body landmark of the person that has already been identified by yolo. The main concept by which inaccurate exercise movements are identified is by considering that different exercises have common mistakes relating to that exercise respectively. Every exercise has a set of rules to maintain its integrity and proper form, if the user violates these rules the system is trained to identify it. The violations are identified as incorrect exercise movements. To determine this, we used the Yolo model which identifies the user frame selected box and each body-landmark which calculates the proper angles for each exercise and the bearing needed to perform them correctly. The function Max Angle has been used on every exercise to determine the maximum angle that a user creates between a certain set of landmarks when an exercise is performed. The Max Angle for each exercise is determined by the maximum angle defined in each exercise by its uniquely placed rules. Technology ensures accuracy and focuses on the intended workout movements through meticulous data collection and preparation using cutting-edge computer technologies like OpenCV and YOLO model. The following algorithm training, which utilizes supervised learning and the Random Forest method, allows the system to recognize and assess exercise movements in real-time. After training, the algorithms are integrated into a mobile application environment so the user can easily use it for their workout routines. Sometimes certain exercises require the user to face their body away from the phone because certain exercises the side angle view to correctly determine if their exercise is being performed correctly. In such instances instant audio feedback is provided since the user will be facing away from their device. This ensures that the user can fully focus on the workout without being distracted and therefore will be able to maintain the correct form throughout the exercise.

D. Personalized Dietary Plan Recommendation

First, detailed, and precise information regarding nutrition from professionals in the field of nutrition and well-known sites. This first set is used to create personalized meal plans that suit specific dietary needs and preferences. To get reliable nutrition data, high quality sources were used while critically evaluating nutritional information. It is important to observe that the quality of this data should be the highest possible because it will form a basis for fine tuning the algorithms of the system and generating successful personal diet recommendations for its users. First, Basal Metabolic Rate (BMR) is calculated to determine the number of calories needed by the body for maintenance of its basic physiological activities at rest. This is done using different formulas for men and women. The formula for men is:

BMR=88.362+(13.397 $\times$ weight in kg) + (4.799 $\times$ height in cm) - (5.677 $\times$ age in years)

While the one for women is:

BMR=447.593+(9.247 $\times$ weight in kg) + (3.098 $\times$ height in cm) - (4.330 $\times$ age in years)

These equations play a significant role in identifying the number of calories required to sustain key body functions like breathing, blood circulation and cell production among others while resting. Following the BMR calculation, its miles adjusted based on the man or woman’s level of bodily hobby to determine the full every day calorie wishes. The adjustment is made using multipliers that vary in keeping with extraordinary interest stages. For instance, the multiplier for sedentary individuals (people with little to no workout) is 1.2. For folks who interact in mild exercise or sports for 1-3 days consistent with week, the multiplier is 1.375. For moderately lively people (those who work out or take part in sports three-five days according to week), the multiplier is 1.55. The multiplier for very active individuals (those who have interaction in hard exercise or sports activities 6-7 days in keeping with week) is 1.725, and for extra active individuals (people with very difficult workout, a physical task, or education twice an afternoon), the multiplier is 1.9. This adjustment ensures that daily caloric consumption should display the person's lifestyle and strength expenditure. To further tailor the caloric intake in step with unique fitness and health dreams, additional adjustments are made. For individuals aiming to preserve their weight, the adjusted BMR is used as a calorie restriction. For the ones in search of weight loss, 500 to one thousand calories are subtracted from the protection price to gain a safe and sustainable weight reduction of about 1 to 2 pounds per week. Conversely, for people aiming to advantage muscle, 250 to 500 energies are added to the maintenance value to guide muscles. An illustrative example can clarify this process. Consider a moderately active 30-year-old woman who weighs 65 kg and is 165 cm tall. Her BMR is calculated as follows:

$$BMR= 447.593+(9.247\times65) + (3.098\times165) - (4.330\times30) \approx 1399 \text{ calories/day.}$$

This BMR is then adjusted for her activity level: Daily Calorie Limit=BMR$\times$1.55$\approx$2167 calories/day.

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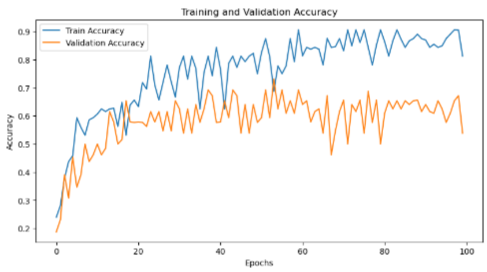
To enhance the precision and personalization of those calculations, a random forest regressor algorithm is hired. This system mastering set of rules considers diverse user-unique facts factors including age, weight, peak, and hobby stage to offer a precise and individualized caloric requirement. The random forest regressor is especially effective due to the fact it can manage non-linear relationships and interactions between capabilities, thus improving the accuracy of the calorie estimates. By incorporating person preferences, the meal plans are more likely to be popular and observed, for that reason enhancing consumer pride and adherence to the weight loss plan. Linear Programming is used to optimize the meal plans to meet each day calorie restrict even as respecting person possibilities and dietary suggestions. The meal plans consist of balanced options for breakfast, lunch, and dinner, ensuring that users obtain numerous nutritious eating regimen. This method not only simplifies the meal planning procedure but also ensures that the nutritional requirements are met without exceeding the caloric limits.

IV. RESULT AND DISCUSSIONS

The selected CNN model to identify the body type had 95% training accuracy and 87% testing accuracy. A high level Keras library was employed in training the CNN model. During the model training process overfitting was observed to nullify this a technique known as dropout regularization was used with varying dropout rates which was effective in the prevention of overfitting. Fig 2 illustrates the Model Accuracy Plot which helps to evaluate the performance of the trained CNN model.



[Fig.2: Model Accuracy Plot]

When the users uploaded their pictures, the system accurately identified if the body type is an ectomorph, endomorph, or mesomorph, then the user was prompted to choose a suitable fitness goal. Then the identified body type, height, weight, and fitness goal was passed on to the workout plan function where a knowledge-based system generated a workout plan. Using the generated workout plan and dietary recommendations, the system predicted a timeline in which the user can achieve their desired body goal based on their choice, the accuracy of the random forest regressor model that was used to generate the timeline was 86% overall. Based on the body type identified a workout plan is given using a large dataset of exercise plans which is classified based on the body type, goal, number of sets, repetitions, duration, week, and applicable music. This dataset was checked by experts in kinesiology science for the safety of data and reliability. Users could view the individualized plan for each session, their progress over time, and grade every exercise once it was completed, with the use of emoji buttons. The UI of the workout plan and emoji-based feedback system was exceptionally clean and user-friendly. The study showed this works for most users who enjoyed the custom exercise schedules. The emoji icon, reflecting end-user feedback, worked satisfactorily. There is a scope to make better the dynamic use of such feedback in modifying future workout plans for example, dissatisfactory exercises could either be replaced by similar exercises training the same muscle groups. Expansion of the dataset of exercises with new and varying exercises will prevent the boredom of doing repetitive exercises and ensure that the interest of the user is retained by specific exercise customization.

When considering and training the results for the exercise movement tracking system with real time feedback, the random forest model an accuracy of 88%. As shown in Table 1, the dataset taken was comprising 135,000 rows of x and y coordinates. The testing accuracy that was achieved was 85%, a slight loss of accuracy was expected as there are challenges in generalizing the learned patterns to new, unseen data. This is due to overfitting during the model training phase. One solution to this is to add more videos and preprocess the dataset to a higher degree. However, the random forest classifier was accurate and successful in identifying the exercises.

Table 1: Classification Table for Random Forest Classifier

Class	Precision	Recall	F1- Score	Support
Bent_Overhand _Row_Dumbbell	0.85	0.90	0.87	75994
Bicep_Curl_to _Overhead_ Press	0.82	0.87	0.84	77103
Body_weight _squat	0.80	0.85	0.82	33997
Dumbbell_Curls	0.78	0.82	0.80	44373
Jumping_Jacks	0.75	0.80	0.77	37391
Accuracy			0.88	268858
Macro Avg	0.85	0.85	0.82	268858
Weighted Avg	0.85	0.88	0.86	268858

Integration of YOLO and Mediapipe significantly increased the systems capability to detect incorrect exercise movements in real time. Yolo correctly identified the user, and the

Media-Pipe was effective in pinpointing the body landmarks in the user, this allowed the system to correctly assess the exercise forms dynamically. The two technologies work in combination to facilitate instant feedback and correct the users' movements.

When considering such an exercise as jumping jacks, the arm should be fully extended not partially, and the person should jump to perform the exercise correctly. Therefore, in the developed model the incorrect exercises are determined using angles and co-ordinates to measure the accuracy of the movement. So, in this case, looking at the angle between the coordinates of the arm using 3 defined set points located at the beginning, middle and the end of the arm, consider the angle created by the 3 points at the beginning middle part and end of the exercise. When testing this it was observed that when the user exceeded the MAX ANGLE between the midpoint and arm which was 165 degrees, the system gave "incorrect" real time audio feedback also this was seen when the MAX ANGLE between the legs and mid-point was increased by 110 degrees. The mobile application has an extremely user-friendly interface that displays key workout metrics for the user. For example, the number of repetitions for each exercise and avatar videos that show the correct forms were two features employed to increase user friendliness. Another key feature is the real time counter, where the users' repetitions are automatically counted and displayed so the user can easily keep track of their workout. The app tracks the user through the exercise and gives feedback directly to the user offering feedback on their form.

In the dietary recommendation system, a BMR calculation was used to provide accurate estimates of necessary energy. For example, a slightly active 30-year-old woman who weighs 65kgs and is 165cms tall has a BMR of approximately 1399 calories per day which when added to activity levels total 2167 calories. Activity level ensures the proper reflection of the user's lifestyle. This is crucial for the purpose of proper dietary plans. Further customization to the recipient of the recommendations is the goal-specific caloric intake adjustments of weight maintenance, loss, and muscle gain. These adjustments can be made, for example, with a safe caloric reduction of 500 to 1000 calories, while an addition can be made with 250 to 500 calories for muscle gain. Moreover, the use of the random forest regressor algorithm to calculate the daily caloric limit improves the accuracy of the algorithm to account for user-specific factors, the accuracy of the model was 85.32%. Linear Programming ensures nutritious and adequately balanced meal plans with nutritionally appealing options for breakfast, lunch, and dinner, giving better health outcomes. Flexible and varied options for breakfast, lunch, and dinner offer the user an alternative to menu planning, offering multiple alternatives helps in accommodating several types of tastes and nutritional restrictions. This paper infused advanced algorithms with user-specific data to develop a personalized fitness and diet planning application. This ensured that the calculations delivered are precise and strong through the combination of the BMR calculation, activity level adjustment, goal-specific caloric adjustments, and machine learning. The inclusion of linear programming and user preferences made the dietary plans more practical and user-friendly, thus promoting healthier lifestyle choices

V. CONCLUSION

In this study, machine learning, computer vision algorithms, and knowledge-based system technologies were used to create a personalized and adaptable fitness application which identified the user based on their body type and provided a personalized and customizable workout and diet plan while also creating a Realtime exercise monitoring system to act as a personal trainer that corrected the users exercise form. Users enhanced their fitness experience and get the highest results possible by optimizing their workout routines, forms, and nutrition. The body type was identified using CNN with an accuracy 87%. Random forest regressor was used to identify the timeline to achieve the fitness goal and to identify exercises with an accuracy of 86% and 88% respectively. In the future enhancement of the accuracy and features to increase and broaden the target market is ideal and recommended.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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