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Intelligent Web-Based Application for Personalized Obesity Management

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ABSTRACT

Obesity is a serious global problem due to its association with various chronic diseases. This study explores the utilization of machine learning in particular deep learning technology to predict Body Mass Index (BMI) from individual photos to create an efficient solution for assessing obesity. Using the ResNet152 model and K-Fold Cross Validation, this application integrates filters on individual photos to improve prediction accuracy. The application was developed using React JS for the front end, PHP and MySQL for the backend and database management, and Python as the core of the machine learning system. The application that tested using blackbox method, to see all features is functioning and the web application prototipe is passed all the test scenario.

I. INTRODUCTION

Obesity is one of the most pressing global health problems. This is because obesity is associated with an increased risk of several serious diseases such as hypertension, type 2 diabetes, coronary artery disease, cancer, and many other health problems [1], [2], [3], [4]. Accurate assessment of obesity levels in the population is important to monitor prevalence and incidence, as well as to assess the effectiveness of population-level interventions. Data from the World Health Organization (WHO) in 2016 showed that obesity has reached alarming proportions globally. About 650 million adults and 340 million children and adolescents were categorized as obese or overweight [5]. These statistics reflect the high prevalence of obesity in both adults and young populations, suggesting the need for a more effective approach to monitoring and addressing obesity issues in society. The problem of obesity is therefore not only a public health challenge but also points to the need for the development of more efficient and accurate methods to measure and manage this condition on a population-wide scale.

Body mass index (BMI) is one of the common measurements used to determine obesity [6], [7], [8], [9], [10], however, this data collection often requires time and specialized measurement equipment that can sometimes result in uncertainty in the assessment of a per son's BMI value. Therefore, alternative measurement techniques that are faster and easier are needed for large population surveys, such as using photographs of individuals to obtain BMI estimates using machine learning. Machine learning technology has opened up a great opportunity to handle such problems efficiently [11], [12]. Through the utilization of datasets containing images of individuals with varying BMIs, models can be trained to predict a person's BMI based on their images.

The creation of this machine learning system application aims to provide an appropriate solution for determining BMI with high efficiency. This application not only has potential as a personal health monitoring tool but is also able to provide recommendations related to exercise and diet. Thus, this application can be a support in maintaining health and taking appropriate action when changes occur in individuals.

To identify complex patterns in data image, deep learning methods will be used. Deep learning has the benefit of being able to extract complex information from massive amounts of data [13], [14]. One deep learning technique that is well-known for processing photos and capturing visual features is the Convolution Neural Network (CNN) algorithm [15]. The rise of CNN-based designs like AlexNet, VGGNet, GoogLeNet & Inception, RestNet, DenseNet, MobileNets, EfficientNet, and RegNet [16]illustrates the growth of CNNs for computer vision problems. This research will use the Resnet-152 architecture to build the model. A residual network that can be tuned for deeper training is included in the ResNet architecture, and this will boost accuracy as training gets more complex [17].

Previous work on computer vision tasks linked to picture classification was done by Latif and Khalifa, who used three Deep Transfer Learning (DLT) algorithms to distinguish between COVID-19, pneumonia viruses, and normal images. The study's findings demonstrate that ResNet50, with an accuracy of 94,72%, offers better training accuracy. Additionally, the ResNet50 model in his study performed well in testing, demonstrating an accuracy score of 80,66% [18].

Next, ResNet-50 was used in research by Shadeed et al. (2018) to diagnose chest illnesses. The model was created to diagnose 15 cases of thorax sickness, including those that were healthy. Three deep models from different research that were built using the same data are compared to see how well the suggested model performs. When compared to three other models that are similar, the model that was constructed performs the best in terms of accuracy for each class. Deeper networks exhibit lower error rates [19].

Therefore, this paper aims to explore the concept and implementation of a BMI prediction system using machine learning technology. This paper will outline the steps required in the development of this system, such as dataset selection, image processing, machine learning algorithm selection, and model performance evaluation.

II. METHOD

A. Datasets Collection

The data sources used are primary and secondary data. Primary data is obtained through direct data collection by the author in the form of photos and information such as the weight and height of Udayana mathematics students. The dataset consist of 200 collected photos of Mathematics Department, University of Udayana. Data collected on 2023.

B. Hardware and IDE Spesifications

Tools that have been used in this research is explained as follows: Visual Studio Code (VSCode) is the code editor used to design the user interface by utilizing React 18.2.0 technology, and the server side of this project is designed using PHP 8.2. Furthermore, to support analysis and implementation, the author utilized the Google Colab platform with the Python 3.10 programming language and macbook air M1 2021 for the hardware.

C. Datasets Preparation and Preprocessing

Datasets is prepared and preprocessing with edge detection and grayscale method to enable the efficient extraction of features that hold important information [20]. The author uses the processed image as a filter to remove the background by changing all its pixel colors to ones and multiplying it by the original image.

Figure 1. Example of Edge Detection

D. Resnet-152 Architecture

This application utilizes the ResNet152 model as the base model for pre-trained feature extraction. Through the K-Fold cross-validation method, the data is separated into train and test groups, allowing the retrieval of features and labels from each fold. The next step is to retrain the features and labels from each fold beforehand to obtain more accurate prediction results. This process allows the model to learn more general patterns from the data by utilizing each fold as part of the relearning process.

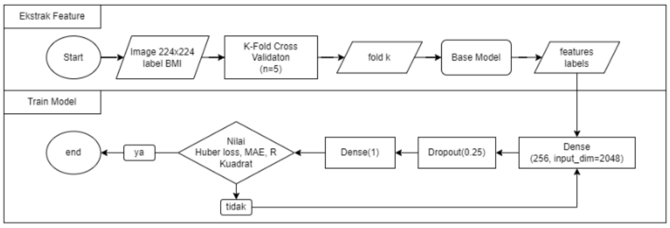

Figure 2. Restnet-152 Architecture

The steps for k-fold cross-validation are as follows:

1) The overall data is divided into k almost equal parts. Then, a series of tests are conducted.
2) In the first iteration, the first part of the data becomes the testing data, while the rest becomes the training data. Here, the accuracy or similarity between the predicted results and the actual data is calculated based on the proportion of the data.
3) The second iteration involves using the second part as testing data and the other part as training data. Accuracy is also calculated based on the proportion of this data.
4) This process continues until it reaches the kth iteration, where the kth part is used as the test data. Accuracy is calculated based on that portion of the data.
5) Next, the average accuracy of the k-test results above is calculated. This average is the final accuracy of the k-fold cross-validation process.

E. *Web Application Design*

The system comprises three core modules: a welcome page (/ endpoint) that serves as the entry point, an authentication module (/auth endpoint) enabling user sign-in and sign-up via secure PHP APIs, and a dashboard module (/dashboard endpoint) that facilitates predictions and analytics. User authentication involves RESTful API requests managed by PHP, while image-based predictions leverage Python-based machine learning models accessed via the /predict endpoint. The results, including prediction outputs and calculated BMI, are stored using PHP APIs (/api/v1/dashboard/post) for subsequent visualization in the dashboard or analytics submodules. This design emphasizes a separation of concerns, ensuring scalability and maintainability, with distinct backend services handling authentication (PHP) and ML-based inference (Python).

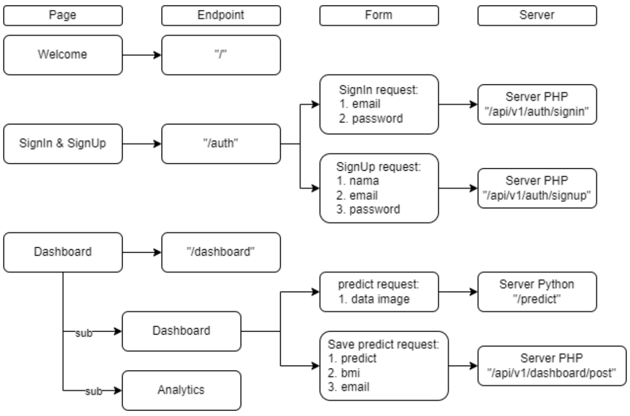

Figure 3. Web Application Design

F. *Database Design*

Database for this web application consists of two tables: users and predict, linked through a foreign key relationship on the email field.

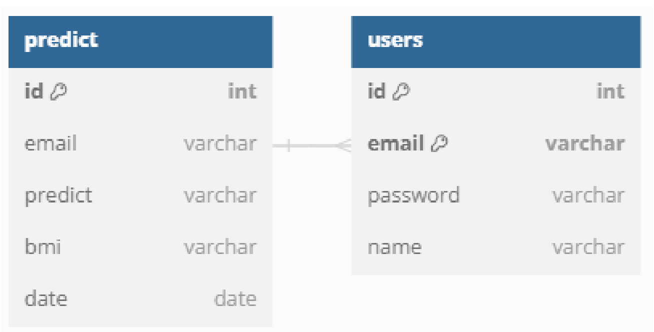

Figure 4. Database Schema

The users table stores user-specific data, including a unique identifier (id), email address (email), password (password), and name (name). The predict table records prediction-related data, where each entry is uniquely identified by the id field and contains the user's email (email), prediction results (predict), calculated BMI values (bmi), and the associated date (date). The foreign key constraint ensures data integrity by linking predictions to registered users via the email field.

G. *API Design*

Four primary endpoints are defined: /api/v1/auth/signup, /api/v1/auth/signin, /api/v1/dashboard/get, and /api/v1/dashboard/post. Each endpoint receives data in JSON format and directs it to specific server-side functions for processing. The handleSignUp function processes user registration data (name, email, password) and returns either a success response (status, text, email) or an error response (error, text). Similarly, the handleSignIn function verifies login credentials (email, password) and responds with authentication status. For dashboard functionalities, handleListDataPredict retrieves prediction records based on the user's email, while handlePostDataPredict stores new prediction data (email, predict, bmi).

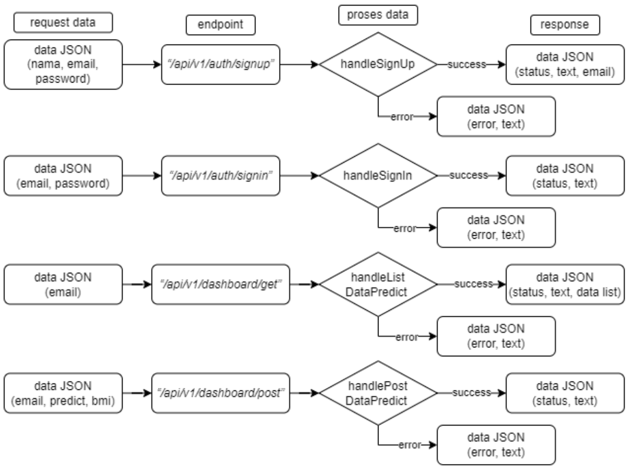

Figure 5. API Design

H. *Overall System Design*

The BMI prediction process is done statistically where it uses a dataset model that has been trained into HDF5 (.h5) format files.

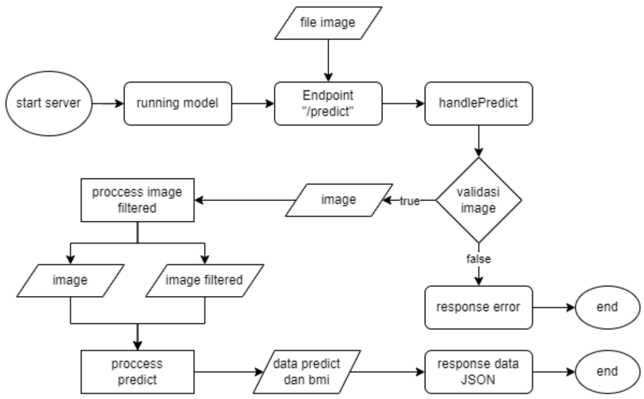

Figure 6. Overall System Design

Then a prediction request handle is created which can be accessed via the "/predict" endpoint. This handle receives requests in the form of image files (jpg, jpeg, png) and responds in the form of data (predict, BMI) in JSON format.

III. Results and Discussion

A. Resnet-152 Model

This research uses input images with a size of 224x224x3 and labels in the form of BMI numbers which will be extracted using the Resnet-152. The detailed implementation of Resnet-152 architecture is as follow:

1) The first layer uses the Dense layer as input from the feature base model which has a dimension of 2048. The filters used are 256 and use the RELU activation function.
2) This process also uses the Dropout value. Dropout is a regulation method used in neural networks to randomly turn off some neurons during the training process, which means they are randomly ignored or disabled. The purpose of this technique is to reduce the possibility of overfitting during the training process.
3) The second layer is the output of the training process. Using a dense layer with several filters, one of which is the numeric of BMI itself. The activation function used is linear.
4) Furthermore, the optimization method used is Stochastic Gradient Descent (SGD) with a learning rate of $10{-}5$ and a momentum of 0.9.
5) Evaluation metrics used are Huber loss function, Mean Absolute Error (MAE), and R-Squered.

B. Resnet-152 Training and Testing Result

The research was conducted by separating the training dataset and test dataset using the K-Fold Cross Validation method so that there is the same output when separating the data. In this study, 5 folds were used so that the output of the model was also as many as five models. The metrics used in this training and testing is Huber evaluation metric, Mean Absolute Error (MAE), and R-Squared respectively. The following are the results:

1. 1st fold result [3.72,4.18,0.27]

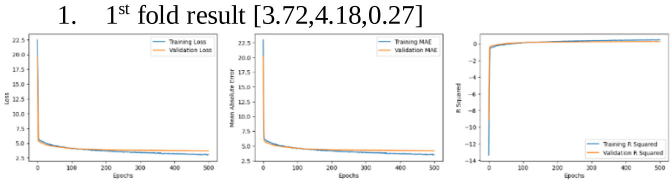

Figure 7. 1st Fold Training and Testing Result

2. 2nd fold result [3.71,4.18,0.25]

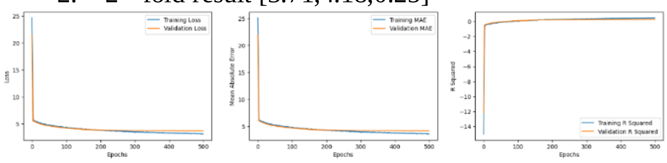

Figure 8. 2nd Fold Training and Testing Result

3. 3rd fold result [3.79,4.26,0.33]

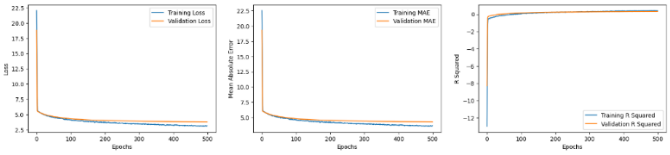

Figure 9. 3rd Fold Training and Testing Result

4. 4th fold result [3.50,3.96,0.312]

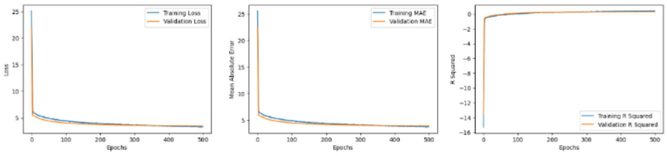

Figure 10. 4th Fold Training and Testing Result

5. 5th fold result [3.77,4.25,0.311]

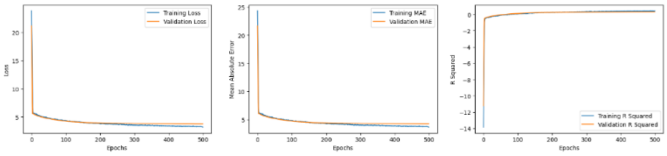

Figure 11. 5th Fold Training and Testing Result

The training and validation plots for the ResNet-152 model utilizing the Huber Loss, Mean Absolute Error (MAE), and R-Squared metrics exhibit a well-performing model with consistent learning behavior. In the first plot (Loss), the Huber Loss decreases significantly during the initial phase of training, stabilizing after approximately 100 epochs and converging towards a lower loss value by the end of 500 epochs. This indicates effective minimization of both large and small errors due to the robustness of the Huber Loss metric, which combines the advantages of mean squared error and mean absolute error. The second plot (MAE) shows a similar trend, with both training and validation MAE progressively decreasing, reflecting an improvement in prediction accuracy as the epochs increase. This alignment between training and validation MAE suggests minimal overfitting, as the model generalizes well across the datasets. The third plot (R-Squared) demonstrates an increasing trend, with values approaching 1.0, indicating a high degree of predictive accuracy and strong explanatory power of the model for both the training and validation sets. Overall, the performance metrics suggest that the ResNet-152 model achieves stable convergence and exhibits good generalization, as evidenced by the consistency in the trends across all evaluation metrics.

C. Resnet-152 Model Out Sample Testing Result

In real world condition, Resnet-152 model is tested by inputing one photo of Udayana University student that have height : 173 cm, weight : 100 kg and BMI : 33,4. The detailed input is shown as follow :

Figure 12. Image of Udayana University Student

Resnet-152 model successfully analyzed the photo and give result :

```
1/1 [==============================] - 0s 98ms/step
1/1 [==============================] - 0s 73ms/step
BMI: 32.26031494140625
Moderately obese
```

Figure 13. BMI Analyzed Result

D. Web Application Implementation

This is the implementation of intellegent web based application for personalized obesity management :

1. Login Page and Register Page

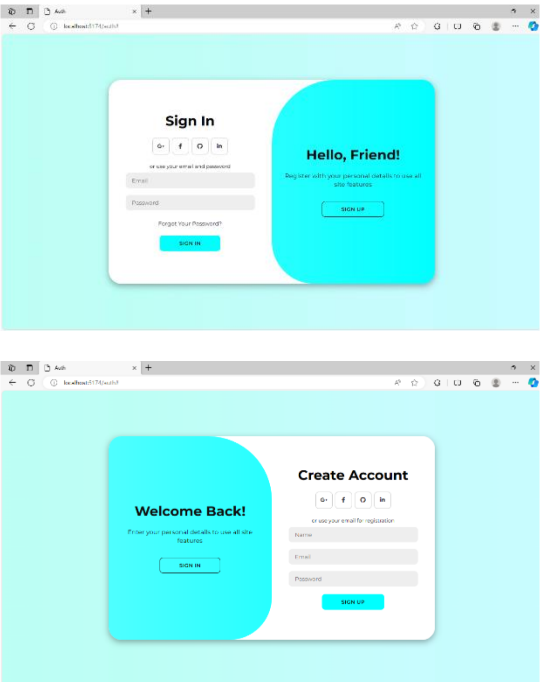

Figure 14. Login and Register Page

2. Dashboard and Prediction Table

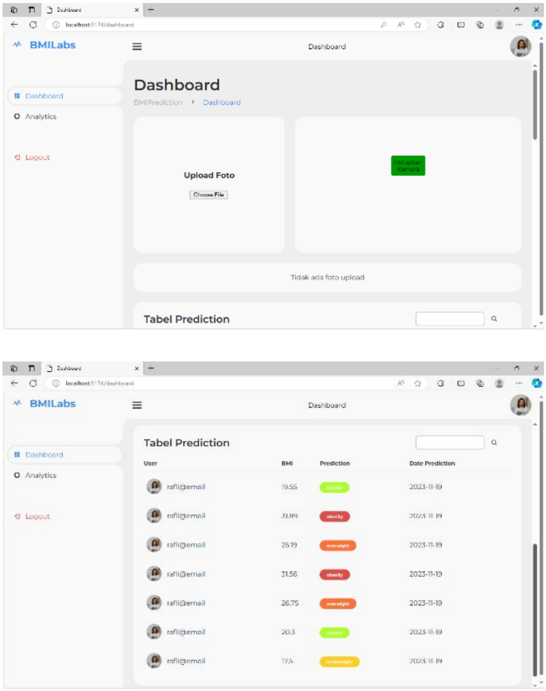

Figure 15. Dashboard and Prediction Table

3. Diet and Workout Recommendation Page

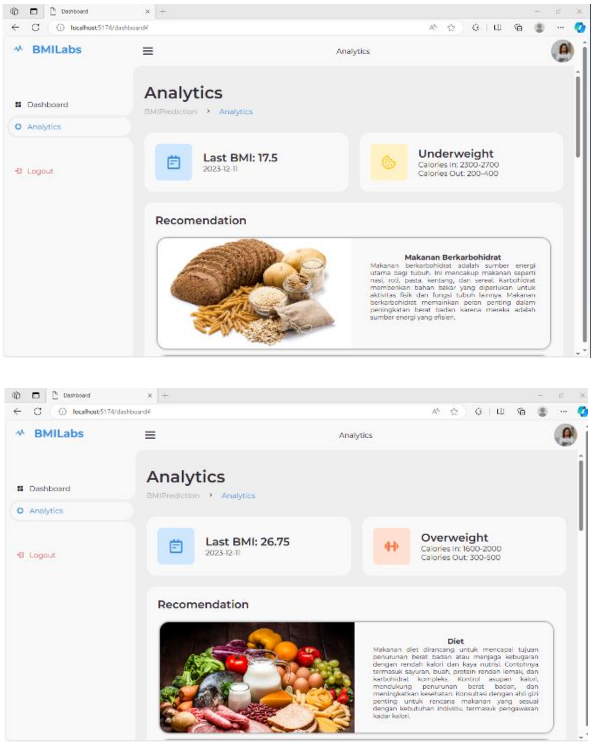

Figure 16. Diet and Workout Recommendation Page

E. Black Box Testing

The black-box testing results demonstrate a comprehensive evaluation of the system's core functionalities. The test scenarios included user registration (BMI-01), user login (BMI-02), image upload and analysis for personalized recommendations (BMI-03), and handling of non-human image uploads (BMI-04).

TABLE I.
INTELLEGENT WEB APPLICATION BLACK BOX TESTING

Test ID	Test Scenario	Actual Result	Status
BMI-01	User registration	User successfully registerd	Passed
BMI-02	User login	User successfully logged in	Passed
BMI-03	Upload and analyzed human images	Human images successfully analyzed and give personalized recommedation	Passed
BMI-04	Upload non human images	System give notification non human images have been uploaded	Passed

All test cases passed successfully, indicating that the system operates as expected under typical user scenarios. Specifically, the system accurately processed user registrations and logins, managed the analysis of uploaded human images to generate personalized recommendations, and correctly identified non-human images, providing appropriate notifications. These results suggest that the implemented features are robust and capable of handling standard user interactions without functional errors.

IV. CONCLUSION

In conclusion, the study successfully implemented the ResNet-152 model for image analysis and prediction, demonstrating its effectiveness in handling complex image data. The inclusion of a filtering process in image preprocessing significantly enhanced the model's focus on human photo objects, leading to improved accuracy in predictions. The model evaluation metrics indicated optimal performance in the fourth fold, achieving a Huber Loss of 3.50, a Mean Absolute Error (MAE) of 3.96, and an R-Squared value of 0.312. These results suggest that the model was able to minimize both large and small prediction errors effectively, although the R-Squared value indicates room for improvement in terms of the model's explanatory power. The black-box testing verified the correct implementation and functionality of all core features, including user registration, login, image upload, and analysis, as well as the handling of non-human image uploads. Overall, the findings highlight the potential of the ResNet-152 model, augmented with image filtering techniques, for accurate and reliable image analysis in real-world applications, though further optimization may be needed to enhance the model's predictive strength as indicated by the R-Squared metric.

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