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Comparison of Regression, K-Nearest Neighbors (KNN) and Multi-Layer Perceptron (MLP) Models for the Prediction of Weight, Gender and Body Mass Index Status

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ABSTRACT
Maintaining good health is challenging, and weight is a significant indicator of health. Individuals with underweight, overweight, or obese tend to suffer from major health issues like diabetes, heart disease, high blood pressure, and cancer. To avoid and control these issues, precise estimates of weight, gender, and BMI status are crucial. This article uses machine learning algorithms like Regression, K-Nearest Neighbor, and Multi-layer Perceptron to predict weight, gender, and body mass index status. The results show that linear regression models can predict weight based on height with around 85% accuracy. KNN performs best when considering gender, with an accuracy score of 91.04%. The MLP model is the most effective in predicting gender from height and weight, with an accuracy rating of 92.07%. Finally, the MLP model surpasses other models in predicting BMI status based on height and weight, scoring 97% accuracy. This study is expected to be beneficial to medical science and public health care.

General Terms
Classification, Prediction, Body Mass Index Status

Keywords
Weight, BMI, Gender, Predict, Machine Learning Algorithms.

1. INTRODUCTION
Weight plays a crucial role in maintaining a healthy life, as underweight or overweight can lead to various health problems such as diabetes, heart disease, high blood pressure, and cancer. Maintaining a balance weight is essential for health safety and blood donation programs, as blood donors must weigh at least 45 kg. Underweight individuals may have a weak immune system, fatigue, and anemia, while overweight individuals may face joint pain, diabetes, sleep apnea, and other health issues.

Gender is another important parameter for weight, as men have a greater weight compared to women due to their different body structures. The ideal weight and height for maintaining a healthy life can vary for men and women, with women having a greater percentage of body fat due to their daily life experiences. Gender-specific rules should be followed to maintain a healthy weight.

Body Mass Index (BMI) is an important parameter in medical science for maintaining a healthy weight. It is calculated by dividing a person's weight (in kilograms) by the square of height (in meters). BMI values are classified into four categories: Underweight, Normal Weight, Overweight, and Obesity. A BMI value less than 18.5 indicates underweight, 18.5 to 24.9 indicate good health, 25 to 29.9 indicate overweight, and 30 or higher indicates obese.

A good healthy weight should be maintained by individuals, and early detection of overweight or obesity can prevent serious health problems. This research paper introduces machine learning approaches to predict weight based on height and gender, gender based on height and weight, and body mass index status (underweight, normal weight, overweight, obese) based on certain parameters. The expectation is that this research will contribute to advancing medical knowledge and public health care.

2. LITERATURE REVIEW
This section describes some of existing research related to this article. As weight and BMI maintaining importance is increasing in medical science for saving human lives, it tends to work by the researcher in this field.

In the research [1], anthropometric data were extracted from two-dimensional images using machine learning algorithms to analyze human body weight. Support vector and Gaussian process regression were used to predict BMI, while multi-class SVM was employed to categorize the data. The mean absolute errors of the two models (SVR and GPR) for calculating BMI from a single image were 3.8 and 3.9, respectively. Furthermore, the SVR and GPR's mean absolute percentage errors are 12.5% and 13.1%, respectively. For BMI estimation, the support vector regression model outperformed the Gaussian process regression model.

For predictions about human health parameters, such as height, weight, and body mass index, this research [2] used machine learning techniques. The deep neural network model achieved mean absolute errors of 0.082, 8.51, and 2.36 for height, weight, and BMI, respectively.

In this article [3] , the authors focused on the prediction of body mass index using a machine learning approach with the internet of things (IoT). This study represents a design based on IoT that can predict if a person's weight is normal or overweight. For this, height is measured using an ultrasonic sensor, and weight is measured using a load sensor. An exponential Gaussian process regression model was used for prediction. This model performed very well, with an accuracy of 99.18%.

For age estimation and gender recognition using machine learning technique, this study [4] utilized facial images. For this challenge, the authors utilized deep CNN combined with transfer learning. First, VGGFace and VGG19 were utilized with transfer learning. Then, age estimation and gender categorization were performed using deep CNN. According to this study, utilizing transfer learning with deep CNN, gender may be classified with a high degree of accuracy of 98.7%. The task of estimating age can also be completed with a mean absolute error of 4.1 years.

The deep Convolutional Neural Network (CNN) model was utilized in this research [5] to predict body mass index. The authors did this by using pictures (silhouette images) of the people. The CNN system predicted BMI values accurately and consistently. With an average of 0.124, the best validation loss was 0.0625. The best result was 0.976, but the average absolute error was frequently 1.66. The average root mean square error (RMSE) was 2.16, with 1.52 being the best result. The CNN regression model performed well for both male and female participants, with correlation coefficients, explained variance, and coefficient of determination being higher in female subjects.

The gender prediction using machine learning was the primary concern of this study [6]. For this, gender classification was done using face-based images. The Kaggle dataset and the Nottingham Scan Database were the two types of datasets used for model training and testing. The CNN model's convolution and pooling layers are responsible for feature extraction. A classifier with fully connected layers was employed to categorize gender. The Adam optimizer and k-fold cross validations were employed to increase accuracy. The study discovered that, when using the trained CNN model, the Kaggle dataset delivered the best accuracy of 97.44% while the Nottingham Scan Database provided 90% accuracy.

The purpose of this research [7] was also to identify gender using a machine-learning approach. The authors recognized gender using speech data. For the analysis of voice data, eight data features were evaluated. Following feature extraction, the LSTM (Long Short-Term Memory) model was used to identify the gender. The accuracy, sensitivity, and specificity metrics were used to evaluate the performance of the LSTM model. This study found that the LSTM model recognizes gender quite effectively, with an accuracy of 98.4%.

The body weight estimation utilizing a machine learning approach was the main emphasis of this study [8] .Two-dimensional body images were used for this. For feature extraction, face image and whole-body images were taken into independent consideration. In this work, the concept of computer vision was applied. For estimating body weight, deep learning with XG boost regression machine learning models were used. The study discovered that when facial photos are taken into account for weight estimate, it performed better (mean absolute error 9.8) than when complete body photographs are taken into account (mean absolute error 18.2).

This study [9] uses a transfer learning strategy to predict gender. For model training and testing, the authors used dental radiograph images. Gender classification was accomplished using transfer learning models (VGG16, Residual Neural Network with 50 layers, and EfficientNetB6). The modeling strategy performed quite well in this research, with a better accuracy of 97.25% for gender classification.

In this work [10], the age and gender of humans were predicted using a few machine learning techniques. This prediction used facial image data. For these tasks, the authors employed deep CNNs and transfer learning techniques. In this research, it came out that the deep CNN with a certain layer organization performed exceptionally well for gender classification, with an accuracy of 94.517%, and for age estimation, with an accuracy of 79.122%. Transfer learning contrasts the performance following feature extraction with the output of a deep CNN model that has been trained. It was discovered that age estimation had a mean absolute error of 4.58 and that gender categorization had an accuracy of 94.94%. The research also examined the performance of various machine learning feature extraction strategies.

The intent of this study [11] was to predict body mass index using machine learning algorithms. The authors looked at predicting BMI using psychological characteristics (depression, anxiety, and emotion suppression; happiness and emotion regulation). The researchers observed that negative psychological variables (depression, anxiety, and emotion suppression) better predict BMI than positive variables (happiness and emotion regulation). That is, if a machine learning model takes negative psychological characteristics with an accuracy of 80%, it performs well. This study made extensive use of typical machine learning models.

The research [12] concentrated on applying machine learning techniques to predict obesity. Then did a comparison study to demonstrate whether strategy is more effective at predicting obesity. The authors of this study used data from a medical facility. They developed an automated approach for predicting obesity. It needs some user input in the form of data. These include the user's gender, age, marital status, physical characteristics, blood pressure, BMI, and manner of life. For predicting obesity, a total of five machine learning models were used. These included Decision Tree, Random Forest, Gradient Boosting, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and SVM. With a 99.05% accuracy rate, the gradient boosting model outperformed the other models in predicting obesity.

3. METHODOLOGY

In a research paper, methodology describes the procedure or method used to conduct the task. This section includes data collection, data analysis, and system implementation techniques and so on. The methodology of the entire process for conducting the study is described below:

3.1 Data Collection

Data collection is a primary step for conducting any research. For this purpose, a dataset was gathered from Kaggle, comprising data from 10,000 individuals, including their height, weight, and gender. The selection of this dataset was based on its reliability as a data source, ensuring the integrity of the data for the research question. Additionally, its previous utilization in other research approaches was examined to enable future comparisons of research results.

3.2 Data Preprocessing

Data preprocessing is an important step for research. This step ensures that the collected data is ready and suitable for analysis. This step involves some tasks such as removing duplicate values in the dataset and handling the missing value and outliers also. In the collected dataset the height was in inches and the weight was in pounds. The height was converted to meters, and the weight was converted to kilograms for the research purpose, enabling the calculation of body mass index and body mass index status accurately. Moreover, two new columns were introduced in the dataset, labeled as Body Mass Index (BMI) and Body Mass Index Status (BMI Status). Then, BMI was calculated for each individual in the dataset using the formula: BMI = Weight (kg) / Height (m) ^{2}. Then, the BMI status was assigned to each individual based on their respective BMI values. For BMI classification, a BMI of less than 18.5 is marked as underweight, 18.5 to 24.9 is marked as normal weight, 25 to 29.9 is marked as overweight, and 30 or higher is marked as obese.

3.2.1 Dataset Analysis

After preprocessing, a refined dataset was obtained. This research utilized a dataset with five columns: gender, height, weight, BMI (Body Mass Index), and BMI Status (Underweight, Normal Weight, Overweight, Obese).

In Table 1, it can be observed that an equal number (50% each) of males and females are present in the dataset, indicating a balanced distribution of gender. The dataset contains individuals with a minimum height of 1.37 meters and a maximum height of 2.00 meters, with an average height of 1.68 meters. Additionally, the dataset includes individuals with a minimum weight of 29.34 kg, a maximum weight of 122.46 kg, and an average weight of 73.22 kg.

Furthermore, the average BMI is calculated to be 25.475306. The BMI status is categorized into four types: "Normal," "Underweight," "Overweight," and "Obesity." In the dataset, there are 4027 individuals with a "Normal" BMI, 42 individuals with an "Underweight" BMI, 291 individuals with "Obesity," and 5640 individuals with "Overweight." It is evident from the distribution table that the majority of the individuals in the dataset (56.40%) fall under the "Overweight" category, followed by the "Normal" weight category (40.27%).

Table 1. Dataset Analysis

Gender	Height (meters)	Weight (kg)	BMI value	BMI Status
Male: 50%	Max: 2.00	Max: 122.46	Max: 33.02	Underweight:0.42%
Female:50%	Min: 1.37	Min: 29.34	Min: 15.44	Normal:40.27%
	Mean: 1.68	Mean: 73.22	Mean: 25.47	Overweight:56.40%
Total Person =10000				Obesity:2.91%

3.3 Feature Selection

Feature selection is the process of determining useful features for expressing the data and excluding features that are unnecessary with redundant information form. In this study, the Pearson coefficient correlation concept will be utilized. A correlation matrix is an easy manner of presenting the relationships between every parameter in a dataset. The linear association between two variables is expressed by the Pearson correlation coefficient. It ranges from -1 to 1, with a value between.

- A strong negative linear correlation between two variables is shown by a value of -1.
- No linear association between two variables is indicated by a 0,
- A strong positive linear correlation between two variables is indicated by a value of 1.

In the dataset, there are 5 variables. These are Gender, Height, Weight, Body Mass Index (BMI), and Body Mass Index Status (BMI Status). Here, Height, Weight, and BMI can easily represent by the Pearson coefficient correlation matrix because these variables are linear. But the gender and BMI body status are a category or non-linear type variable

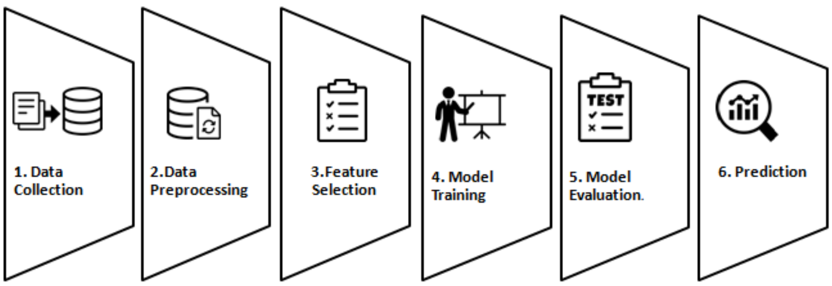

Fig 1: Overview of the Research Approach

To represent these variables, the hot encoding technique needs to be applied. The technique can convert gender-type data to binary data. For gender category (Male and Female) type data, we could create two binary variables, Gender_Male and Gender_Female. These binary variables take the value 1 if the data is matched in that category or 0 otherwise 1. In this way, we can establish the correlation matrix with height, weight, and BMI. In the same way, we can convert the Body Mass Index Status (Underweight, Normal, Overweight, and obesity) into binary data. The Pearson coefficient correlation matrix reveals a strong positive correlation between height and weight, with a value of 0.92. This correlation can predict weight based on height. A moderate positive correlation exists between height and BMI, with a value of 0.67 and 0.90, respectively. Gender also has a moderate positive correlation with height, weight, and BMI, with values of 0.69, 0.80, and 0.76, respectively. The BMI status variable has mixed correlations with height and weight, with higher BMI indicating overweight and obesity, and lower BMI indicating underweight and normal weight.

3.4 Model Training

Model training is crucial in machine learning studies. This section describes how to train Regression, K-Nearest Neighbors (KNN), and Multilayer Perceptron (MLP) models to predict weight, gender, and BMI status. The Jupyter Notebook application was used for model training, and the dataset was split into training and testing sets using an 80:20 or 70:30 split ratio. The Regression, K-Nearest Neighbors, and MLP models were defined and initialized for each predicting task. The scikit-learn library was used for regression and K-Nearest Neighbors models, while the MLPRegressor function was used for multi-layer perceptron models. The K-Nearest Neighbors model used the K and Euclidean distance metrics for each task. The optimization algorithm was used for regression and KNN, and iterations were defined for multi-layer perceptron models. After successful training, model weights were saved for future use.

3.5 Model Evaluation

Model evaluation is the process of using various metrics to assess the performance of machine learning models in predicting weight, gender, and BMI status. After training, models like Regression, K-Nearest Neighbors, and Multi-layer Perceptron are evaluated for their performance in predicting these data. Evaluation metrics include Mean Squared Error (MSE), R-Squared (R^2), Precision (precision) and recall (recall), F1-score (F1-score), Accuracy (accuracy) and Confusion Matrix (total number of true positives, false positives, true negatives, and false negatives for each type). These metrics help determine the model's effectiveness in explaining observed data and ensuring its suitability for specific tasks.

3.6 Prediction

After model evaluation using metrics such as Mean Squared Error (MSE), R-Squared (R2), Precision, Recall, F1-score, Accuracy, and Confusion Matrix, we used the best model to predict weight, gender, BMI, and BMI status**.**

4. EXPERIMENT RESULTS AND DISCUSSION

In this study, five different types of tasks have been conducted. These tasks are related to predicting the many health parameters of humans based on their height, weight, and gender. The first task is predicting the person's weight based on their height. The second task is the extended version of the first task. This is predicting the weight based on height and gender. The third task covers that, predict the person's body mass index based on their weight. The fourth task includes that; predict the person's gender based on their height and weight. And the fifth task is predicting the person’s body mass index status based on height and weight.

4.1 Predict the Person’s Weight based on Height

For predicting a person's weight based on height, the study employed three models: Linear Regression model, K-Nearest Neighbors model, and Multi-layer Perceptron model. Figure 2 illustrates the performance of these models in predicting weight based on height. A slight difference is observed among the three models in their weight prediction capabilities.

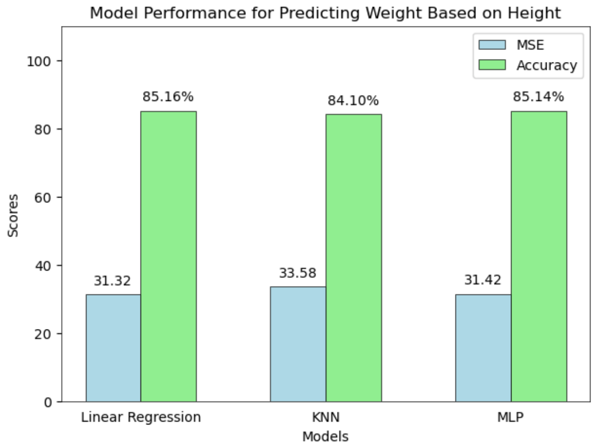

Figure 2: Model Performance for Predicting Weight based on Height.

The Mean Square Error (MSE) values indicate that the Linear Regression model achieved the lowest MSE of 31.32, followed closely by the MLP model with an MSE of 31.42. However, the K-Nearest Neighbors (KNN) model had a higher MSE of 33.58 compared to the other two models. That means the linear regression model and MLP model perform well to predict weight based on height. Linear regression model have the higher accuracy (85.16%) compare to other two models.

4.2 Predict the Person’s Weight based on Height and Gender

The Figure 3 compares the performances of multiple linear regressions, KNN, and MLP models to predict weight based on height and gender.

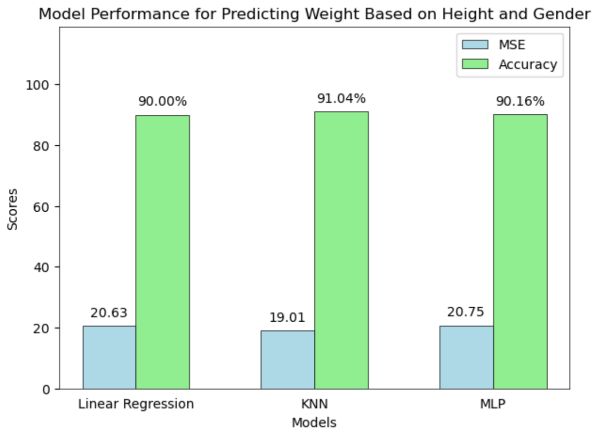

Figure 3: Model Performance for Predicting Weight Based on Height and Gender

The K-Nearest Neighbors (KNN) model exhibits the lowest MSE of 19.01, closely followed by the multiple linear regression model with an MSE of 20.63. In comparison, the Multi-Layer Perceptron (MLP) model shows a higher MSE of 20.75 compared to the other two models. That means K-Nearest Neighbors (KNN) model performs well to predict weight based on height and gender. KNN model have the higher accuracy (91.04%) compare to other two models.

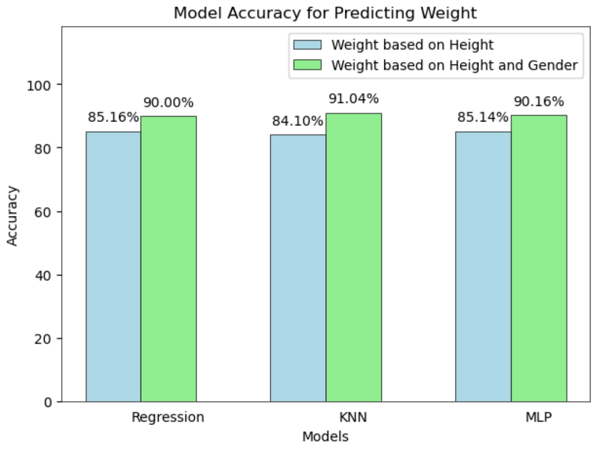

Figure 4: Compare the Task-01 and Task-02 Performance for Predicting Weight

Based on Figure 4, when predicting weight solely based on height, the linear regression model achieves an accuracy of 85.16%. However, when predicting weight considering both height and gender, the K-Nearest Neighbors model demonstrates higher accuracy, reaching 91.04%. This indicates that incorporating height and gender as features provides a more reliable approach for weight prediction, leading to improved accuracy levels.

4.3 Predict the Person’s Body Mass Index (BMI) based on Weight

To predict a person's Body Mass Index (BMI) based on weight, three models were used: Linear Regression model, K-Nearest Neighbors model, and Multi-layer Perceptron model. Figure 5 illustrates the performance comparison of these models in predicting BMI based on weight. A marginal difference is observed among the three models in their BMI prediction abilities.

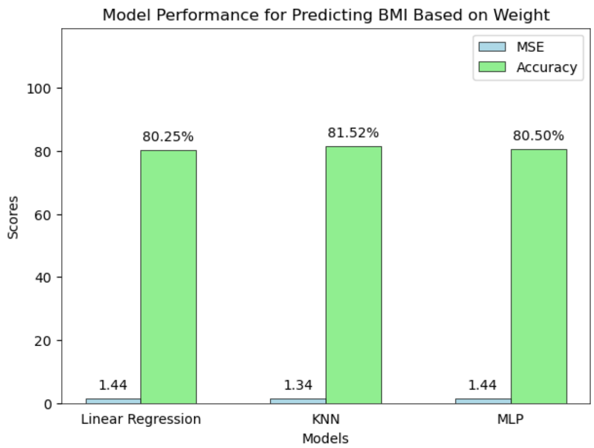

Figure 5: Model Performance for Predicting BMI Based on Weight

After analyzing the Mean Square Error (MSE) values, it was found that the K-Nearest Neighbors (KNN) model achieved the lowest MSE of 1.34, while both the linear regression model and Multi-Layer Perceptron (MLP) model obtained an MSE of 1.44. This indicates that the K-Nearest Neighbors (KNN) model performs well in predicting BMI based on weight. Moreover, the KNN model exhibited a higher accuracy of 81.52% compared to the other two models.

4.4 Predict the Person’s Gender based on Height and Weight

For predicting the person’s Gender based on height and weight, Logistic Regression model, K-Nearest Neighbors model and Multi-layer Perceptron model were used. The Figure 6 shows the representation of the classification report of these three models in a chart.

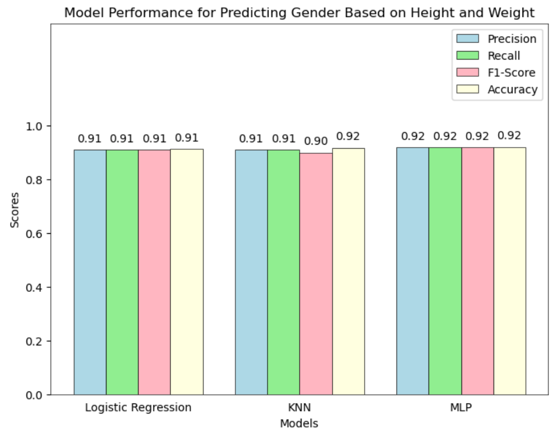

Figure 6: Models Performance for Predicting Gender Based on Height and Weight

From the results displayed in Figure 6, it is apparent that the precision, recall, f1-score, and accuracy of each model are quite similar. Yet, upon closer examination of the classification report, the multi-layer perceptron model stands out with a higher macro average f1-score (0.92) and accuracy (0.9207) compared to the other two models. As a result, selecting the MLP model based on the macro-average F1 score is suggested for Gender prediction utilizing Height and Weight data.

4.5 Predict the Person’s BMI Status based on Height and Weight.

For predicting a person's BMI Status (underweight, normal weight, overweight, or obesity) using height and weight as predictors, three models were utilized: Logistics Regression model, K-Nearest Neighbors model, and Multi-layer Perceptron model. Notably, the traditional BMI formula was not used during the training process. Instead, the focus was on evaluating the models' prediction accuracy in diagnosing BMI status solely based on height and weight data. As a result, the models were not explicitly provided with the exact BMI ranges associated with underweight, overweight, normal, and obese categories. The classification report presented in Figure 7 depicts the performance of these three models in predicting BMI status based on height and weight.

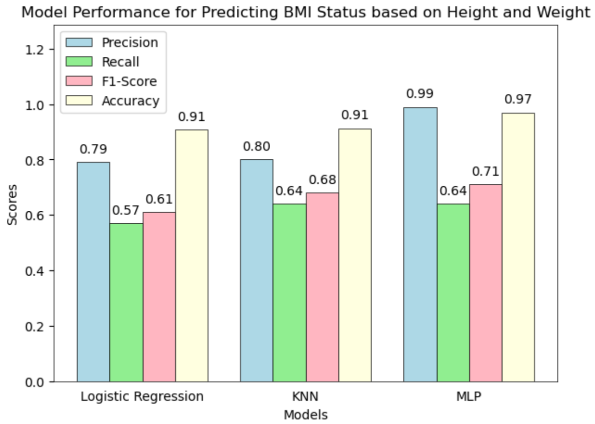

Figure 7: Model Performance for Predicting BMI Status based on Height and Weight

Based on the classification report's graphical representation, it is clear that the multi-layer perceptron model outperformed the other two models in terms of overall average f1-score (0.71) and accuracy (0.97). The MLP model is the best choice for predicting BMI status based on height and weight when the macro-average F1 score is taken into account.

4.6 Comparing Performance in Weight, Gender, and Body Mass Index Prediction with Existing Research

In terms of weight prediction, Table 2 shows that this study performs effectively, with a mean absolute error of 3.46, compare to [1] , [8] and [2] which have mean absolute error (MAE) of 3.80, 9.80 and 8.51 respectively. In that scenario, the K-Nearest Neighbor (KNN) model was utilized, considering height and gender as parameters. The performance might differ due to the use of straightforward numerical and text parameters (Height in Meters, Gender: Male/Female). It is known that height exhibits a strong correlation with weight, and males tend to have more height compared to females. As a result, the model achieved excellent performance, yielding an accuracy of 91%. However, existing research considers facial and full body image-based data for weight prediction, which could potentially lower the accuracy of those models.

For gender prediction, in the Table 3, this research [4] is performed well with accuracy 98.7% considering the parameters of facial images compare to [7] , [9], [6] which have the accuracy 98.4% , 94.94% , 97.25% , 97.44% respectively.

Table 2. Performance Comparison with Existing Research for Weight Prediction

Research Paper	Applied Model ,Which Performed Best	Parameters	Result (Mean Absolute Error)
[8]	Deep learning with XG boost regression	Facial Images, Full Body Images	9.80
[1]	Support Vector Regression (SVR)	Full Body Images	3.80
[2]	Convolutional Neural Network: RestNet50	Facial Images	8.51
This Study	K-Nearest Neighbors(KNN)	Height and Gender	**3.46** Accuracy: **91%**

This study have the less accuracy (92%) compare to these existing research for gender classification and prediction.

Table 3. Performance Comparison with Existing Research for Gender Prediction

Research Paper	Applied Model ,Which Performed Best	Parameters	Model Accuracy
[10]	Deep CNN	Facial Images	94.94%
[4]	Deep CNN + Transfer learning(VGG19 and VGGFace)	Facial Images	**98.7%**
[7]	Deep LSTM Networks	Voice Data	98.4%
[9]	Transfer learning models (VGG16, ResNet50, and EfficientNetB6)	Dental Radiograph Images	97.25%
[6]	Deep CNN model	Facial Images	97.44%
This Study	Multi-layer Perceptron (MLP) model	Height and Weight	92.07%

The research was conducted for gender prediction based on height and weight. The majority of existing research primarily relies on image-based data, particularly male/female face images, as they provide better inputs for gender prediction. As a result, the approach used in this research, which is based on height and weight inputs, is comparatively less accurate than the methods utilizing image-based data in the existing research.

For Body Mass Index (BMI) prediction, it is observed that in Table 4 , this research [3] is performed very well with an accuracy 99.18% that means, it almost predicted the BMI correctly every time. This IoT based design used Exponential Gaussian process regression model for the prediction. This research [12] also performed very well with accuracy of 99.05%. The proposed model in this study for estimating BMI value and BMI status also performed well. With weight as a parameter, the K-Nearest Neighbor model has an accuracy of 81.52% for predicting BMI values. The Multi-layer Perceptron Model also predicted BMI Status (Underweight, Normal, Overweight, and Obesity) extremely well, with an accuracy of 97%.

Table 4: Performance Comparison with Existing Research for Body Mass Index (BMI) Prediction.

Research Paper	Applied Model , Performed Best	Parameters	Model Accuracy
[12]	Gradient Boosting.	Gender, Age, Family history, Blood Pressure, Body Mass Index, and Daily activity.	99.05%.
[13]	Multi-Layer Perceptron (MLP)	Age, Gender, Height and Weight	93.96%
[11]	Support Vector Machine (SVM)	Psychological variables (Depression, anxiety, and happiness).	85%
[5]	Deep CNN	Silhouette images of the people	97.6%
[3]	Exponential Gaussian process regression model	Height and Weight	**99.18%**
This Study	BMI value Prediction using KNN	Weight	81.52%
	BMI Status Prediction using MLP	Height and Weight	97%

5. CONCLUSION

This research aims to predict weight, gender, and body mass index status using a well-balanced dataset and machine-learning approaches. Three well-known algorithms (Regression, K-Nearest Neighbor, and Multi-layer Perceptron) were used, considering various parameters for weight prediction, gender classification, and body mass index status prediction. The Multi-layer perceptron model performed well with 97% accuracy, while K-Nearest Neighbor achieved 91% accuracy for weight prediction and 92.07% for gender prediction.

In the future, additional factors, including age, physical characteristics, lifestyle factors, and genetic markers, may be further investigated to improve predictions. By using a variety of data sources, such as facial pictures, 3-D body scan images, and audio data, prediction accuracy may be improved. Additionally, the use of innovative methods for machine learning like ensemble approaches (Random Forests, Gradient Boosting), as well as advanced algorithms like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), opens up new possibilities for enhancing predictive abilities. The potential for these improvements to produce more accurate and reliable predictions of body mass index status, gender, and weight will eventually progress this field of study.

5. REFERENCES

[1] M. Jiang and G. Guo, "Body Weight Analysis From Human Body Images," in IEEE Transactions on Information Forensics and Security, vol. 14, no. 10, pp. 2676-2688, Oct. 2019, doi: 10.1109/TIFS.2019.2904840.

[2] A. Dantcheva, F. Bremond and P. Bilinski, "Show me your face and I will tell you your height, weight and body mass index," 2018 24th International Conference on Pattern Recognition (ICPR), Beijing, China, 2018, pp. 3555-3560, doi: 10.1109/ICPR.2018.8546159.

[3] G. M. Mark, P. Bakunzibake and C. Mikeka, "Design of an IoT-based Body Mass Index (BMI) Prediction Model," 2021 4th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI), Yogyakarta, Indonesia, 2021, pp. 629-634, doi: 10.1109/ISRITI54043.2021.9702866.

[4] P. Smith and C. Chen, "Transfer Learning with Deep CNNs for Gender Recognition and Age Estimation," 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, 2018, pp. 2564-2571, doi: 10.1109/BigData.2018.8621891.

[5] A. Pantanowitz, E. Cohen, P. Gradidge, N.J. Crowther, V. Aharonson, B. Rosman, and D.M. Rubin, "Estimation of Body Mass Index from photographs using deep Convolutional Neural Networks," Informatics in Medicine Unlocked, vol. 26, pp. 100727, 2021. [Online]. Available: https://doi.org/10.1016/j.imu.2021.100727.

[6] T. A. Sumi, M. S. Hossain, R. U. Islam, and K. Andersson, "Human gender detection from facial images using convolution neural network," in Applied Intelligence and Informatics: First International Conference, AII 2021, Nottingham, UK, July 30–31, 2021, Proceedings, vol. 1, pp. 188-203, Springer International Publishing, 2021.

[7] F. Ertam, "An effective gender recognition approach using voice data via deeper LSTM networks," Applied Acoustics, vol. 156, pp. 351-358, 2019. https://doi.org/10.1016/j.apacoust.2019.07.033.

[8] M. Jiang and G. Guo, "Body Weight Analysis From Human Body Images," in IEEE Transactions on Information Forensics and Security, vol. 14, no. 10, pp. 2676-2688, Oct. 2019, doi: 10.1109/TIFS.2019.2904840.

[9] İ. Ataş, "Human Gender Prediction Based on Deep Transfer Learning from Panoramic Dental," arXiv preprint arXiv:2205.09850, 2022. [Online]. Available: https://arxiv.org/abs/2205.09850.

[10] V. Sheoran, S. Joshi, and T. R. Bhayani, "Age and gender prediction using deep CNNs and transfer learning," in Computer Vision and Image Processing: 5th International Conference, CVIP 2020, Prayagraj, India, December 4-6, 2020, Revised Selected Papers, Part II, vol. 5, pp. 293-304, Springer Singapore, 2021.

[11] G. Delnevo, G. Mancini, M. Roccetti, P. Salomoni, E. Trombini and F. Andrei, "The Prediction of Body Mass Index from Negative Affectivity through Machine Learning: A Confirmatory Study," Sensors, vol. 21, no. 7, pp. 2361, 2021.

[12] M. F. Anisat, F. D. Basaky and E. O. Osaghae, "Obesity Prediction Model Using Machine Learning Techniques,"

Journal of Applied Artificial Intelligence, vol. 3, no. 1, pp. 24-33, 2022.

[13] B. Singh and H. Tawfik, "Machine learning approach for the early prediction of the risk of overweight and obesity in young people," in Computational Science–ICCS 2020: 20th International Conference, Amsterdam, The Netherlands, June 3–5, 2020, Proceedings, Part IV, vol. 20, pp. 523-535, Springer International Publishing, 2020.