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An Artificial Neural Network-Based Approach for Predicting Obesity Risk

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ABSTRACT

Obesity can be defined as a medical condition associated with the excess accumulation of fat, and it has been reported to be a major cause of mortality & morbidity, cardiovascular diseases, and diabetes. Early detection of obesity is of utmost importance to mitigate the long-term health challenges associated with this disease, necessitating the development of accurate and reliable diagnostic models. This study's primary focus is to develop a neural network model with the capacity of predicting patients' obesity status with high precision and accuracy. The study used a public dataset sourced from the Kaggle database; it comprises 2,111 patient records with 16 input features. The dataset was preprocessed and analyzed using various statistical techniques, which include exploratory analysis and correlation analysis. The exploratory analysis reviews the high prevalence of obesity risk associated with age and weight. The correlation analysis shows that the majority of features had a significant statistical relationship (p-value < 0.05). Physical activity of patients (FAF), SCC, Usage of technology (TUE), CAEC, and NCP all showed a weak negative and significant relationship with the obesity status of patients. A cost-sensitive weighing strategy was employed in this study to mitigate issues of class balancing of the target variable; this method enables higher weights to be assigned to minority classes. The proposed artificial neural network used in this study is made up of two hidden layers, and it was trained using the Adam optimizer over six distinct learning rates. The training results review that the ANN attained its optimal accuracy of 96.2% using a learning rate of 0.01, and it outperforms previous Machine learning algorithms used by previous studies in predicting obesity risk in patients. This study demonstrates the effectiveness of ANNs in detecting obesity status and underscores their importance as decision-support tools for clinicians to enable early intervention and personalized treatment. Future research should consider incorporating broader socio-economic and lifestyle factors and

larger real-world datasets to further enhance model generalizability and applicability in diverse healthcare settings.

Keywords: Machine learning, Obesity risk prediction, Artificial Neural Network

1.0 INTRODUCTION

Obesity remains one of the most significant global health challenges, and it has been attributed to the accumulation of excess fat defined as BMI ≥30 kg/m² (Mushtahid S. et al. 2023). Mushtahid S. et al. (2023) stated that the prevalence of the disease doubled in both developed and developing nations after the 1980s. Obesity has been observed to be connected to both mortality and morbidity, cardiovascular diseases, diabetes, and certain types of cancer (K. Smith & M. Smith, 2016; G. Raina, 2011). Early identification is crucial for mitigating long-term health complications associated with obesity (V. N et al., 2025; G. Russu et al., 2017). Machine learning algorithms trained using clinical data can accurately bridge the gap in the detection of obesity risk, enabling timely intervention (V. N et al., 2025). Artificial neural networks a subset of Machine learning have been observed to detect obesity accurately, particularly in children and adolescents. ANNs have been observed to outperform traditional techniques like BMI and waist circumference in detecting obesity, attaining an accuracy score of 97% (Mohammad D., 2021). Chubarov et al., (2022) reported that ANNs were able to predict obesity risk in younger adults using factors such as age, BMI, sex, and Family obesity status. He (2022) compared the ANN to a tree-based model (Decision Tree) and highlighted that both algorithms attained an accuracy score of over 90% in detecting obesity risk in patients. These findings underscore the potential and significance of applying ANNs in detecting obesity. The primary aim is to develop and evaluate an ANN-based model for detecting the obesity status of patients using a diverse dataset comprising demographic, behavioral, and lifestyle variables.

This paper is structured as follows: Section 2.0 explores the performance and report of recent studies in relation to predicting obesity risk; Section 3.0 discusses the study proposed approach; Section 4.0 focuses on the results performance of the proposed approach using the selected performance metrics considered in this study; Section 5.0 discusses the significance of the model in comparison with previous studies; and Section 6.0 presents the study conclusion.

2.0 RELATED STUDIES

This section of explores the various machine learning algorithms used in recent studies in detecting obesity risk in patients. Mahmut Dirik (2023) carried out a comparative study analysis using eleven machine learning algorithms to predict the obesity status of patients. The algorithms include Multilayer Perceptron (MLP), Support Vector Machine (SVM), Fuzzy K-Nearest Neighbors (FuzzyNN), Fuzzy Unordered Rule Induction Algorithm (FURIA), Rough Sets (RS), Random Tree (RT), Random Forest (RF), Naive Bayes (NB), Logistic Regression (LR), and Decision Table (DT). The study concluded that Random Forest classifier attained the highest accuracy (95.78%) for detecting the obesity status of patient, followed by the logistic regression (95.22%). Hanifatus et al. (2025) develop a predictive model for detecting obesity using five machine learning algorithms which include K-Nearest Neighbors (K-NN), Naïve Bayes Classifier (NBC), Decision Tree, Random Forest, and Support Vector Machine (SVM). The study showed that Random Forest algorithm had the best performance with an accuracy of 92.29%, followed by Decision Tree at 90.54%, K-NN at 83.44%, and NBC and SVM which reached 59.15% and 59.08%, respectively. Elias et al. (2021) develop a model for predicting overweight and obesity using Machine learning algorithms. The study utilizes ML algorithms like Decision Tree, Support Vector Machines, K-Nearest Neighbors, Gaussian naive bayes, Multilayer Perceptron, Random Forest, Gradient boosting, and Extreme Gradient Boosting. The study results reviews that the Random Forest was the most optimal model yielding an Accuracy score of 77.69%. Olutimehin et al. (2023) predicted the risk of obesity in patients using a US health dataset. The study employed the BMI as a proxy for predicting the obesity risk in patient using Machine learning algorithms like Linear regression, Random Forest Regressor, and XGBOOST regressor. The study concluded that the RF regressor was superior with an R-squared score of 1.000. Nima et al. (2023) explore the effectiveness of Decision trees, Support Vector Machines, and Neural Networks in Obesity risk. The study employed a SMOTE algorithm for addressing issues of data balancing of the target class. The study employed a cross-validation technique in training the ML algorithms. The study noted that the ML algorithms all attained high accuracy scores Extreme Gradient Boosting (98.18%), CatBoost Classifier (98.18%), Random Forest Classifier (97.27%), Gradient Boosting Classifier (97.27%), Light Gradient Boosting Machine (97.27%), and Logistic Regression (95.45%). Wei et al. (2023) explored the use of Machine learning Algorithms in detecting obesity in Chinese patients using CatBoost algorithm. The study results shows that the Catboost attained an accuracy score of 83% on the test dataset. Thamrin et al. (2021) examined the risk factors for obesity using data sourced from Indonesian Basic Health Research. The study utilizes a ML approach using NB, LR, and CART (Classification and Regression Trees). The study discovered that the Linear Regression model was the most efficient model for this particular use case. Pang et al. (2021) explored the use of HER dataset in detecting obesity in children. The study employed the use of seven ML algorithms, and it noted that XGBOOST was the best model with an accuracy score of 66.14%. Rodríguez et al. (2021) developed an ML based approach for predicting overweight and obesity in patients. The study utilizes 16 features related to physical conditions including a diet. The study concluded that the GXBOOST and RF attained the best accuracy score of 78%. Montañez et al. (2017) used genetic profiles to predict Obesity using ML algorithms. The study ruled that SVM attained the best accuracy of 90.5%, surpassing decision tree, decision rule, and k-NN. Zarindokht Helforoush and Hossein Sayyad (2024) investigated the effectiveness of using a hybrid metaheuristic machine learning approach in predicting obesity risk in patients. The study employed the use of ANN-PSO (Particle Swarm Optimization) algorithm, and seven ML algorithms. The study results reviews that the ANN-PSO surpassed the other ML algorithms with an accuracy score of 91.79%. Maria et al. (2023) utilizes seven Machine learning algorithms in predicting obesity risk. The ML algorithms include KNN, SVM, Random Forest, Ada Boost, Gradient

Boosting and XGBOOST. The study concluded that the Gradient Boosting model was the superior model with an accuracy score of 97%.

3.0 METHODOLOGY

3.1 DATA DESCRIPTION

The dataset used in this research is based on the eating habits and physical conditions in relation to the obesity status of individuals from Mexico, Peru, and Colombia. The dataset contains 16 predictor features, one target (class) variable, and 2111 records. The target variable was labelled Obesity and contains 7 distinct classes, namely: Insufficient Weight, Normal Weight, Overweight Level I, Overweight Level II, Obesity Type I, Obesity Type II, and Obesity Type III. Table 1.0 below describes the data features.

Table 1.0: Data description

Feature	Feature type	Description
Gender	Categorical	Patient Gender
Age	Continuous	Patient age
Height	Continuous	Height of patient
Weight	Continuous	Weight of patient
Family history with overweight	Binary	Overweight status of family members
FAVC	Binary	Do you eat high caloric food frequently?
FCVC	Integer	Do you usually eat vegetables in your meals?
NCP	Continuous	Number of meals eaten daily
CAEC	Categorical	Number food eaten between meals
SMOKE	Binary	Smoking status
CH2O	Continuous	Amount water drank daily
SCC	Binary	Daily calories status
FAF	Continuous	Physical activity status
TUE	Integer	Frequency usage of technological devices
CALC	Categorical	Frequency of alcohol consumption
MTRANS	Categorical	Mode of transportation
Obesity (Target)	Categorical	Obesity status

Figure 1.0: Obesity distribution

3.2 DATA PREPROCESSING

Data preprocessing is a critical step in developing effective Machine learning algorithms for predictive analysis. Figure 2.0 shows the workflow strategy used in the implementation of the proposed neural network for predicting the obesity risk of patients. It included the data preprocessing techniques, which include data cleaning for addressing the issues with missing values, feature encoding, and feature scaling for enhancing the performance of the predictive model (Fan et al., 2021; García et al., 2016; Abdel et al., 2024; Nagalpara et al., 2024). The categorical features encoded in this study include Gender, FAVC, FCVC, Smoke, SCC, CALC, MTRANS, CAEC, and Obesity. The Data splitting was used to improve the model performance and generalization (Wu et al., 2012; Wu et al., 2013). The Data splitting strategy employed in this study was 80:10:10, implying 80% used for training, 20% used for validation, and 10% used for evaluating the effectiveness of the proposed artificial neural network.

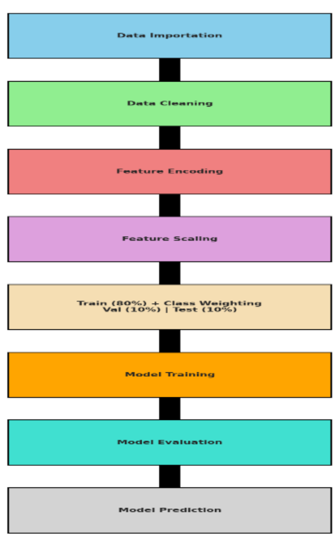

Figure 2.0: Workflow Diagram of the Predictive Modeling Process.

3.3 COST SENSITIVE WEIGHTING STRATEGY

For this study, a class-sensitive weighting technique was utilized to balance the obesity class distribution. This weighing strategy was done to improve the classification of minority class samples (Ünlü, 2020). Khan et al. (2025) stated that this strategy outperforms baseline algorithms and popular data sampling techniques. In the context of this study, this technique was implemented using the Scikit-learn library in Python by assigning higher weights to minority classes.

3.4 ARTIFICIAL NEURAL NETWORK

The neural network input layer used in this study was fitted using 16 input features which consists of patient's demographics, lifestyle and behavioral factors related to the target variable. The input features were preprocessed using techniques stated in section 3.2. Weights w^I are allocated using a random process to each predictor input feature with an added bias b^I. The first and second hidden layer are made up of 256 and 128 neurons respectively, which are passed through a non-linear activation function called ReLu activation function $a^{(l)}$.

X = [X_{GENDER}, X_{AGE}, X_{HEIGHT}, X_{WEIGHT}, $X_{FAMILYHISTORY}$, X_{FAVC}, X_{FCVC}, X_{NCP}, X_{CAEC}, X_{SMOKE}, X_{CH2O}, X_{SCC}, X_{FAF}, X_{TUE}, X_{CALC}, X_{MTRANS}]^T

$$Z^1 = xw^1 + b^1 ------1$$

$$ReLU(z) = max(0, z) ------2$$

$$a^{(l)} = ReLU\left(z^{(l)}\right) = \left(0, W^{(l)}a^{(l-1)} + b^l\right) ------3$$

The output layer was used to predict the probability distribution across 7 obesity status classes, initiated using a SoftMax activation function, which is used for multi-classification (Wasef & Rafla, 2021).

$$\widehat{y_k} = Softmax(Z_k^3) = \frac{e^{Z_j^{(3)}}}{\sum_{j=1}^{7} e^{Z_j^3}} --------4$$

This study used a categorical cross-entropy function for minimizing the training loss of the neural network architecture. Equation 5 represents a categorical cross-entropy function.

$$L(\hat{y}, y) = -\sum_{k=1}^{7} y_k \log(\widehat{y_k}) \text{ ------ } 5$$

Where $\hat{y}, and\ y$ are the predicted label and true label. A back propagation strategy was used to update the weights and bias of each hidden layer in the neural network with respect to the loss. To regulate this process, an Adam optimizer was used to control the learning rate of the process. Equations 6, 7, and 8 show the gradient computation at the output layer, and the gradient with respect to the activation functions of the hidden layers and the loss.

$$\frac{\partial \widehat{y_k}}{\partial z_k} = \widehat{y_k} * (1 - \widehat{y_k}) ----6$$

$$\frac{\partial Relu(z)}{\partial z}\{1\ if\ z > 0\ 0\ if\ \leq 0\ ----7$$

$$\delta^{(3)} = \hat{y} - y ----8$$

While Equations 9 and 10 show the weight and bias updating process using a learning rate of α.

$$W^{(l)} \leftarrow W^{(l)} - \alpha \frac{\partial L}{\partial W^{(l)}} - - - - 9$$

$$W^{(l)} \leftarrow W^{(l)} - \alpha \frac{\partial L}{\partial b^{(l)}} - - - - 10$$

3.5 MODEL EVALUATION

Table 2.0: Performance metrics

Metrics	Description	Formula
Accuracy	It measures the ratio of correct classification acquired using the model prediction (Obi, 2023).	$\frac{TP + TN}{TP + FP + TN + FN}$
Precision	It measures the ratio of positive observations predicted correctly out of all the positive observations (D. Banerjee, Vinay Kukreja, 2023).	$\frac{TP}{TP + FP}$
Recall	It measures the proportions of the total positive predictions captured by the model (Željko, 2021).	$\frac{TP}{TP + FN}$
F1-score	It measures the accuracy of positive predictions using the precision and recall score of the model (Željko, 2021).	$2 * \frac{\text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})}$

TN= True Negative, TP = True Positive, FN = False Negative, FP = False Positive

4.0 RESULT FINDINGS

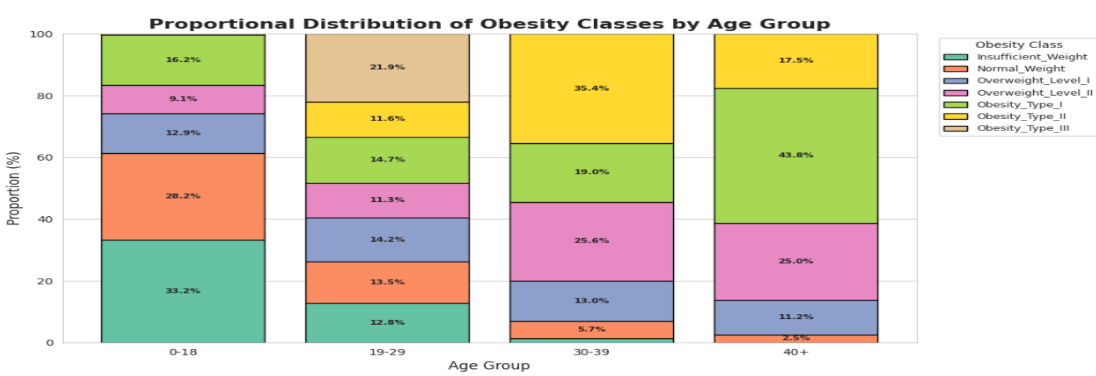

Figure 3.0: Obesity distribution by age group

The results in Figure 3.0 show that the Obesity distribution for age group 0-18 years indicates a combined 61.4% falls within the insufficient weight and normal-weight classes. While, just 16.2% of the patients under this age group were obesity-type I, with 12.9% and 9.1% being overweight level I and II respectively. This suggests that underweight and normal weight status are predominant for this age group. However, a combined 38.6% of the patients were observed to be categorized as overweight or obese indicating a potential health risk for this age group. Furthermore, age groups 19- 29, 30- 39, and 40+ all show similar pattern in increase in overweight and obese related status of patients. This indicates an upward trend in excess weight prevalence across all age groups.

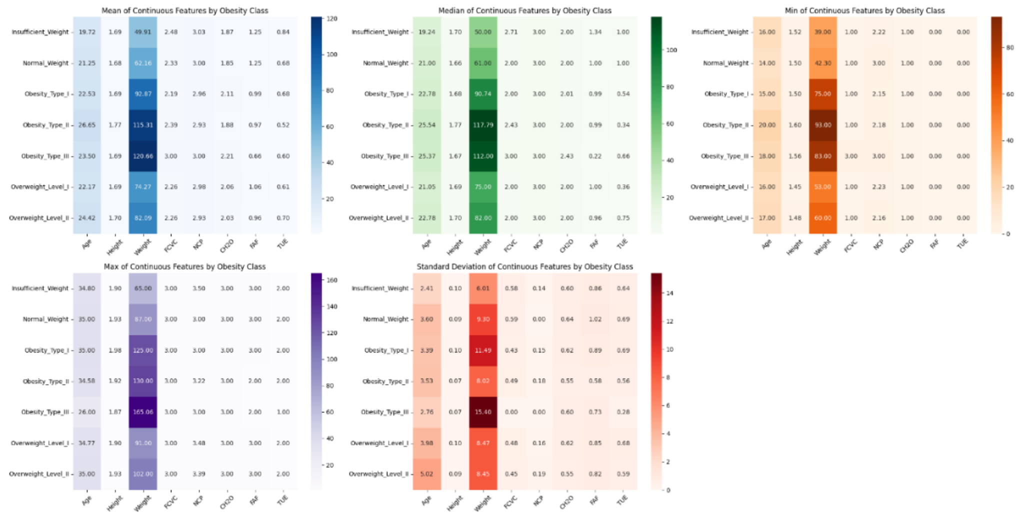

Figure 4.0: Heatmap for the summary statistics

Figure 4.0 shows the summary statistics of the continuous features that include Age, Height, Weight, FCVC (Frequency of Consumption of Vegetables), NCP (Number of Main Meals), CH2O (Consumption of Water), FAF (Physical Activity Frequency), and TUE (Time Using Technology). The results show that the age and weight of the patients show higher values for the obese and overweight classes, indicating that these variables are highly associated with obesity. Also, the distribution of the features was assessed using the mean and median values. For instance, it was observed for age, the obesity status indicated that Overweight Level II (24.42 yrs vs 22.78 yrs), Overweight Level I (22.17 yrs vs 21.05 yrs), Obesity II (26.65 yrs vs 25.54 yrs), Normal weight (21.25 vs 21 yrs) and Insufficient weight (19.72 yrs vs 19.24 yrs) all had a right skewed distribution. It implies that the majority of the patients' ages for this target class were below their respective averages. The patient's heights show minimal differences between the mean and median values, indicating slight skewness in terms of their distribution. The Weight variable shows that Normal weight, Obesity type I, Obesity type III, and Over-weight level II classes were all skewed to the right, with the majority of the values below the average weight of the patients in these instances. CH2O and NCP showed an overall left-skew distribution, indicating that most of the patients' consumption of water and main meals were above the mean reported values across the target classes. Also, it was observed that the overweight and obese patients showed higher consumption.

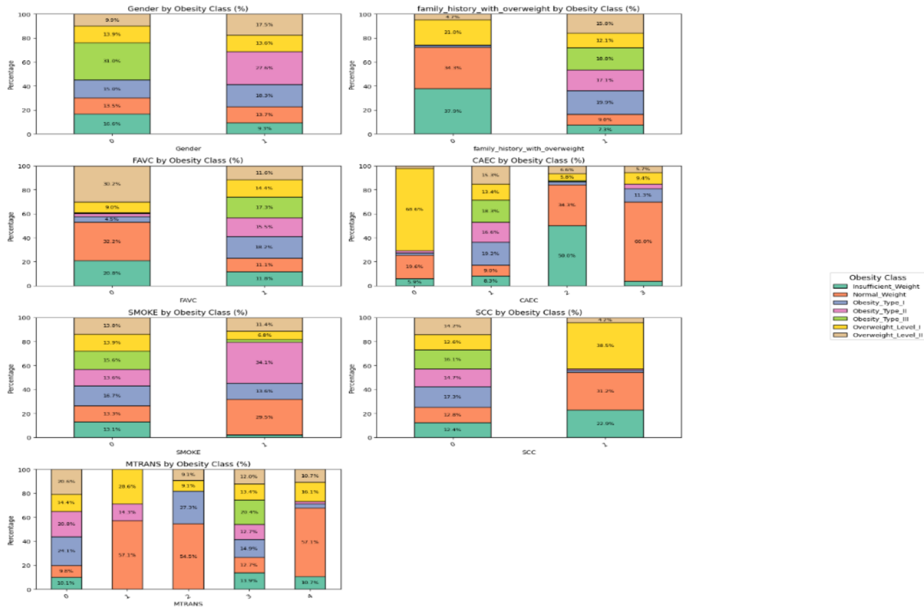

Figure 5.0: Distribution of the obesity classes across the categorical features

The results in Figure 5.0 show that females showed a higher prevalence of obesity than males, while patients with a positive family history of overweight were found to be associated with overweight and obesity status. While patients who consume higher caloric food were observed to be associated with a higher risk of obesity type I and II. Patients found to eat more meals between meals showed a higher prevalence of obesity. Non-smokers and patients who don't monitor caloric intake were also found to show a high risk of obesity. The mode of transportation indicated that patients who did not consider walking or biking have higher chances of being obese and overweight.

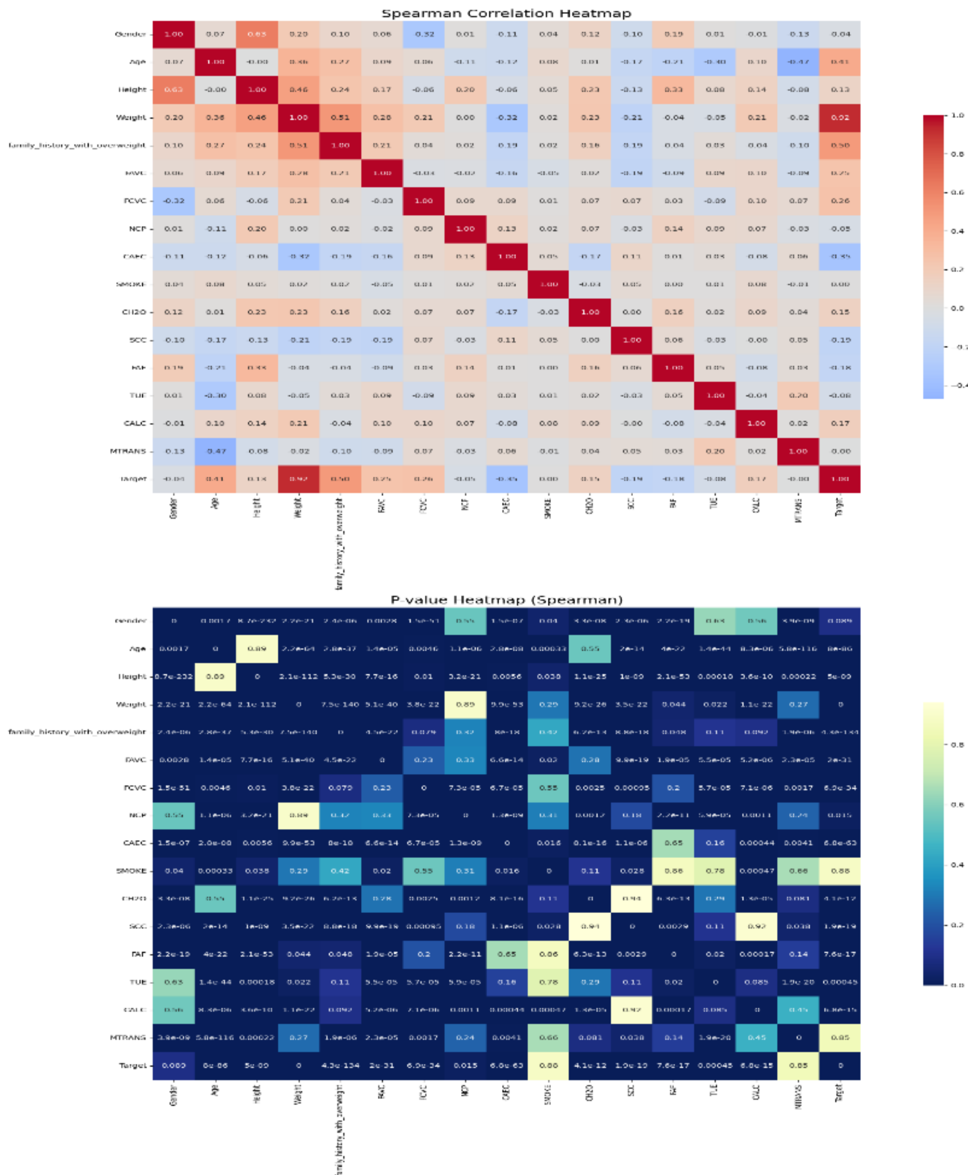

Figure 6.0: Correlation heatmap

Figure 6.0 shows the linear relationship and its significance level between the predictor variables and the target variable. A strong positive and significant ($\rho = 0.92, p - value = 0.0000 < 0.05$) relationship was observed between the weight of the patient and the obesity class, suggesting a body weight is the strongest predictor variable for detecting obesity. Also, a moderately positive and significant ($\rho = 0.41, p - value = 8e - 86 < 0.05$) relationship was detected between age and the obesity status of patients indicating that a higher prevalence of obesity aligns with older patients. There is also a moderately positive and significant ($\rho = 0.50, p - value = 4.3e - 134 < 0.05$) relationship between the obesity status of patients and the family history of overweight. This indicates that hereditary factors are associated with a higher risk of obesity in patients. Other factors such as Height, FAVC, FCVC, CH20, and Calcium level of patients show a weak positive and significant relationship with the obesity status of the patient's indicating that an increase in these factors is associated with a higher prevalence of obesity. On the other hand, the CAEC which is a measure of the number of meals eaten between meals, Physical activity of patients (FAF), SCC, Usage of technology (TUE), and NCP all showed a weak negative and significant (p-value < 0.05) relationship with the obesity status of patients. This implies that a potential decrease in any of these factors is associated with the obesity status of patients. Gender and smoking status of patients were observed to have an insignificant relationship (p-value > 0.05) with the obesity status of patients, indicating that they are not vital factors for determining the obesity status of patients.

Table 3.0: The neural network accuracy across different learning rates

Learning rates	**0.000001**	**0.00001**	**0.0001**	**0.001**	**0.01**
Accuracy	42.0%	67.5%	91.5%	93.9%	96.2%

The results in Table 3.0 show the overall performance of the neural network across different learning rates in terms of accuracy, and it indicates that the learning rate parameter plays a significant role in determining model performance. The results show that the model yielded poor accuracy using a lower learning rate of 10e-6 (42.0%), and 10e-5 (67.5%). This suggests that the neural network was unable to converge optimally using these learning rates. As the learning rates were increased to 10e-4, 10e-3, and 10e-2, the neural performance showed a higher accuracy score of 91.5%, 93.9% and 96.2% respectively. The overall results state that the neural network attains its best convergence and performance in terms of accuracy using a learning rate of 0.01 and this model was used in this study classifying the patient's obesity status.

Tabel 4.0: Best model (learning rate = 0.01) classification report

Status	**Precision**	**Recall**	**F1-score**	**Overall Accuracy**
Insufficient Weight	1.000	1.000	1.000	0.962
Normal Weight	1.000	0.897	0.945	
Overweight Level I	0.900	0.931	0.915	
Overweight Level II	0.933	0.966	0.949	
Obesity Type I	0.946	1.000	0.972	
Obesity Type II	0.967	0.967	0.967	
Obesity Type III	1.000	0.970	0.985	

Table 4.0 shows the classification report for the optimal ANN fitted using a learning rate of 0.01. The results reveal that the model attained a recall score as high as 100% for both the insufficient weight class and the obesity type I class. This result indicates that the neural network in these cases was able to capture 100% of these instances. However, the precision score stating the ability of the model to predict these instances accurately shows that the insufficient weight class had 100%, while that of Obesity type I was 94.6%. Slightly lower recall and precision score were noted for predicting the Obesity type III (97.0%, 100%), Obesity II (96.7%, 96.7%), Overweight level II (96.6%, 93.3%), Normal weight (89.7%, 100%) and

Overweight level I (93.1%, 90.0%). These results show the robust neural nature in capturing these distinct classes with high precision and accuracy.

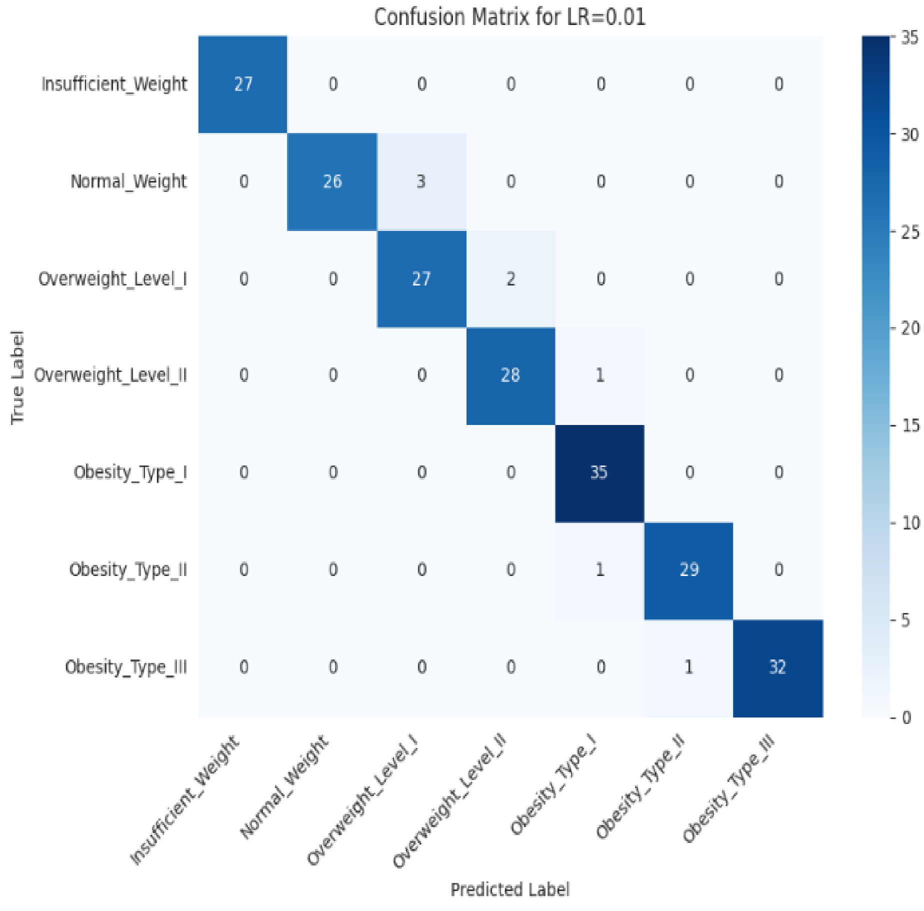

Figure 7.0: Confusion Matrix of the Best Model

Figure 7.0 shows the neural network confusion matrix, which further elaborates the performance metrics of the model. A high diagonal dominance aligns with neural network high recall scores in Table 3.0. However, minor misclassification was noted for the non-adjacent classes except for the normal weight class and the obesity type I class.

Table 5.0: Comparative performance with Recent Studies

Author(s)	Algorithms	Accuracy
Kivrak (2021)	CNN	82% (CNN)
Qahtani et al. (2021)	RF, MLP	95.06% (MLP)
Huang (2022)	RF, Logistic Regression (LR), SVM	95.60% (RF)
Cui et al. (2021)	LR, SVM, KNN, ID3 decision tree, CART, RF, XGBoost,	86.29% (Aggregate Prediction)

	GBDT, LightGBM, Aggregate Prediction	
Jindal et al. (2018)	RF	89.68% (RF)
Lopes et al. (2021)	SVM linear, RF	95.20% (RF)
Sukru Kitis, and Hanife Goker (2023)	SVM, RF, MLP	95.78% (
Hanifatus et al. (2025)	Random Forest, NBC, SVM, Decision Tree, K-NN	92.9% (RF)
Mahmut Dirik (2023)	Multilayer Perceptron (MLP), Support Vector Machine (SVM), Fuzzy K-Nearest Neighbors (FuzzyNN), Fuzzy Unordered Rule Induction Algorithm (FURIA), Rough Sets (RS), Random Tree (RT), Random Forest (RF), Naive Bayes (NB), Logistic Regression (LR), and Decision Table (DT)	95.78% (RF)
Proposed Method	**Feature-scaling + Class-weight-balancing + ANN**	**96.2%**

5.0 DISCUSSION

This provides a credible insight into the use of neural networks as a predictive tool in detecting patient obesity risk status. The study's initial exploratory statistical analysis (See Figure 3.0) on the patients' age demography shows a higher prevalence of insufficient and normal weight for age group 0-18 years, yet a substantial proportion of 38.6% was observed to be associated with overweight and obese status. These findings suggest the need for proactive measures that target the younger population so as to prevent obesity progression into Adulthood. An upward trend in the risk of overweight and obesity was detected for higher age groups, indicating that obesity prevalence increases progressively with age (Low et al. 2009). This trend is concerning as it is associated with insulin resistance, metabolic syndrome, and a decrease in Life expectancy (Muzino et al. 2004; Jura & Kozak, 2016). Furthermore, the summary statistics review shows that age and weight are associated with obesity. This aligns with findings made by Zhang-bin Yu et al. (2011), which states that there is a significant association between these two factors. Also, the distribution of these variables reveals that most of the patients observed in this research were above their average values. Figure 5.0 shows that females were more prone to obesity than males. This aligns with findings made by (Grantham & Henneberg, 2014), and the authors attributed this risk to estrogen's influence on fat accumulation in females. The correlation analysis revealed that body weight had a strict positive and significant ($\rho=0.92$, $p<0.05$) relationship with obesity status, similarly age ($\rho=0.41$, $p<0.05$) and family history ($\rho=0.50$, $p<0.05$) showed a mid-positive and significant correlation with the risk of obesity ($\rho=0.41$, $p<0.05$). Conversely, Physical activity and the number of meals eaten between meals were observed to have a weak and significant negative relationship with obesity status. These results align with findings made by

Saucedo-Molina et al. (2015), who highlighted a significant relationship between Physical activity, food intake, and BMI.

The neural network model's performance across different learning rates shows that its accuracy increases with an increase in the learning rates used in training the model. This result indicates that a decrease in training learning rates improves both accuracy and generalization of the model, as stated by Ding (2021). The Artificial neural network attained a maximum accuracy of 96.2% using a learning rate of 0.001. This indicates that the appropriate selection of learning contributes to a better model generalization and performance (D. Wilson & T. Martinez, 2001). The model performance metrics show that the model attained an average precision and recall score of 96.2% and 96.1% respectively. This indicated that the neural network had minimal misclassification of the distinct obesity classes considered in this study. Table 4.0 shows the results of a comparative analysis that indicates the performance of our proposed method compared to recent algorithms used in detecting obesity using a similar dataset. This shows the effectiveness of employing feature encoding, feature scaling, and cost-sensitive weighting in improving the neural network generalization and accuracy over other compared algorithms like Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN) used by previous authors.

6.0 Conclusion

This study explores the use of artificial neural network in accurately predicting the obesity status of patients using certain lifestyle and demographic features. The study through the use of exploratory and correlation analysis spotted trends between age, weight, and family history as significant factors associated with obesity status of patients, aligning with recent studies and establishing the significance of these variables for predictive modelling. The proposed neural network attained an accuracy of 96.2% using learning rate of 0.001, outperforming several existing machine learning algorithms used by Kivrak (2021), Qahtani et al. (2021), Huang (2022), Cui et al. (2021), Jindal et al. (2018), Lopes et al. (2021), and Sukru K. & Hanife G. (2023). These model predictive performance shows the significance of data preprocessing, hyperparameter tuning and class weight balancing in building robust model for predicting obesity (Harika et al. 2023; Mahadi et al. 2024). This study shows significance of integrating neural networks in enabling clinicians, and health workers alike detect obesity proactively, and develop personalized treatment schemes to manage the health risk associated. It is recommended that future studies should adopt the use of other factors that include lifestyle variables and socio-economic variables to improve the model's generalizations and interpretability in capturing obesity under different contexts. The integration of big real-world datasets in training neural networks should be key in exploring the potential in addressing public health issues and reducing the prevalence of obesity amongst patients.

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