Deep Learning in Adolescent Obesity Prevention: A Path to Health

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Abstract. In this present study, cross sectional data was used to conduct the analysis to research the relationship between BMI and WC on 321 adolescent boys and girls. The data collected by the system was then examined by subjecting it to secondary analysis where complex statistical models and techniques were applied together with deep learning to generate the models needed to predict those at risk for obesity and it was found that the system had a 0.96 accuracy for obesity risk predicted. First of all, the model confirmed that males performances indicated more variance than females, which could be considered reasonable as the proposed model possessed the accuracy of 0.9561 for boys and boys 0.9423 for girls . These results stress the utility of a gender sensitive approach to the prediction of obesity and underline the necessity of different interventions in both the genders. This has made it possible to produce individual tailored answers, and the chance to start early intervention and preventive steps to help the patient in the area of prevention. Gender differences in the prediction of obesity mean that adjustments need to be made in an attempt to help both boys and girls, or in overall, the group of adolescents by reducing the prevalence of obesity , the health of the younger generation has received a boost. As for the gender disparity of obesity rates, the program enabling the health professionals to better aim the interventions.

Keywords: Health Data Analytics, Predictive Modeling, Obesity Prevention Strategies, Health Informatics, Behavioural Interventions, Nutritional Assessment, Deep Learning.

1 Introduction

Context and Significance of Adolescent Obesity: Child and adolescent obesity has become one of the most critical public health issues around the world. The global health analysis done by WHO found that the number of overweight or obese children and adolescents of age five to nineteen years rose from 11 million in 1975 to 340 million in 2020[2][3]. Such risks for their health at such really longevity associated with adolescent obesity is alarming, as obesity in adolescents makes them obese in adulthood.The risks for severe health complications rise and the quality of life is significantly reduced In view of these statistics and possible related diseases [2]. Role of Early Intervention: It means that early detection enables health professionals to map out effective intervention to manage and treat a condition and encourage behaviours that are beneficial and in tandem, discourage behaviours that compromise the health of the individual [1][8]. Such measures do not only enhance the patientвЂ™s health status during the period but will also go a long way in building the patientвЂ™s health status for the rest of his/her life. It has been evidenced that early intervention can help adolescents develop better practices that can be sustain throughout adulthood and help them avoid obesity issues Through use of programs den use one can perform a detailed analysis of a multitude of health related information with a great level of precision Most critically this kind of analysis is beneficial when coming up with patterns that would otherwise not be easily spotted through other forms of analysis [5][7]. Deep learning can handle a range of data such as EHR, genetic data, lifestyle data among others to rank the diverse health conditions for instance, learn in-depth model in the context of obesity prediction including physical activity, dietary habits and demographics In as much as, deep learning has the ability to predict various health outcomes, it informs the healthcare professionals that given individuals who are at high risk of chronic diseases early enough, timely interven- tion is possible to prevent diseases[4][9]. Advancements in Technology: Furthermore, in deep learning, it is possible to analyze a large number of data which makes it possible to intervene as and when required by a certain learner. Therefore, applying the results of the predictive model, it is possible for the healthcare professional to provide recommendations that would provisionally match the particular disease, the patientвЂ™s preferences, and potential situations[7][12].

Table 1: Projected Global Rotundity Trends by Gender of Children, Adolescents, and Grown-ups (2020вЂ“2035) [8]

Year	Children (Boys)	Children (Girls)	Adolescents (Boys)	Adolescents (Girls)
2020	10%	9%	15%	10%
2025	12%	10%	17%	12%
2030	15%	12%	19%	15%
2035	18%	15%	22%	18%

The utilisation of this individualised approach improves intervention utility while strengthening health independence resulting in an eventual improvement on health status Due to its ability in providing accurate prediction of health status as well as providing health interventions to individuals, deep learning has a central role in todayвЂ™s health care [8][13]. As due to the feature of analyzing the broad data it is one of the valuable tools in the continuous process of enhancing the patient care and encouraging health promotion the current research frequently fails to address the fact that health are determined by many aspects Its prediction accuracy and efficiency are relatively low[9][11].Interventions must therefore not only search for at-risk patients but it should also advise on the options suitable for the patient under consideration and his lifestyle.Potential Impact: Thus, by focusing on individual level interventions that incorporate a variety of health factors, it is aimed at improving on the current diffusion of management of adolescent obesity and вЂў The probabilities depict the imaged fat rates of separate demographic groups in the specified(2025- 2035) times. вЂў The data depicted show trends calculated regarding the prophetic model and previous studies done on rotundity pitfalls concerning the different periods and gender[2][11]. creation of pathways to a highly effective management of the problem[7]. Through this study, we want to create a foundation for such advancements that can in fact enhance the lives of youth with potential inclination towards excessive weight gain. Furthermore, this study will investigate gender difference in the prediction of obesity with the aim of de- termining whether boys or girls will have different results and risk factors towards obesity [10]. By examining these differences it is possible to identify critical aspects that will help in design of selective measures based on gender needs [11]. It is hence important to understand these differences so as to formulate intervention strategies which will be appropriate to reach youth and facilitate shift towards healthy life styles [4] In the end, therefore, what this study seeks to do is enhance the possibility of identifying and containing obesity in adolescence so as to enhance the health prospects as well as enable youthful people to live healthy lives into the future.[6][11]

1.1 Related work

Experimental application of different methodologies and frameworks in the field of obesity prediction through AI and deep learning has come a long way in enhancing the current understanding of obesity and obesity prevention. Recent research works have used decision trees, support vector machines, and traditional neural networks AI and machine learning techniques in making predictions about peopleвЂ™s health, proving that these models may be most helpful in helping to flag high-risk candidates. However, following the newest trends in deep learning equipment, it is possible to mention that CNNs and RNNs have been offering much higher results in comparison with machine learning models because of the ability of the first ones to extract intricate features and dependencies to work with. OBESITY RESEARCH CROSS SECTIONAL R E V I E W In addition, other longitudinal studies that focus on trends of obesity among children and adolescents have also enriched the modeling of temporal data emphasizing the evolution of obesity and companion diseases. These works illuminate how obesity risks interact with age, growth processes, and shifts in life cycle; a better model must therefore regard health data as transient.

Other factors than methodological, which play critical role in obesity prediction models include, quality of data used in constructing the actual models. Other measures have been used by researchers to obtain information about diet, physical activity and other aspects of the participantsвЂ™ health, using surveys, wearable devices and mobile applications. Every approach offers specific benefits, as well as the opportunities of real-time activity monitoring using wearable gadgets or the inclusiveness of self- questionnaires, yet bear specific threats concerning data credibility and the participantsвЂ™ adherence to instructions. Feature selection and feature engineering are very important while building strong predictive models, as inclusion of some vital health parameters like BMI, daily intake, sleep cycle, even genetic make-up also help in giving a better model. Different deep learning platforms and structures have been investigated for obesity estimation as presented below: Convolutional Neural Networks (CNNs): CNNs are ideal for image-based applications such as analyzing dietary images for nutritional analysis Deep Learning: Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks: These networks are appropriate for analyzing health data sequences over time. Despite the success of these models, the integration of personal health interventions has become may be a potential approach to apply predictive modelling results. Research has indicated that targeted approaches which are guided by an identified expected risk level can help to reduce the obesity levels vastly especially for teens. Such interventions may include individualized nutrition and physical activity guidelines, counseling on behavior modification, assessment of such obesity indicators as blood pressure and cholesterol level, which makes these interventions more effective. This latter result implies that the best model should not necessarily be an overall one, but selected based on factors such as the size of the data set, and how it is going to be used. Moreover, incorporation of social demographics of income level, education level and neighborhood has also been found to improve model performance and A sharper understanding in view of the fact that these factors play a strong role in determining such parameters as lifestyle and access to the healthcare system.

2 Materials and Methods

2.1 Experimental protocols for data Acquisition

The researchers description of the aims of the study was given where emphasis was put on the consequences of the study that may assist in combating obesity among teenagers. While presenting the rationale for the study, the group underlined possibilities of the research for students, such as studying their health behaviour and encouraging them to lead healthy lives. The reason for sharing this was simply to enlist their support as principals; it is was needed to gather participants. The research team with the cooperation of principals and teachers in the chosen schools intended to provide favourable learning conditions and stimulate involvement of students and their parents[8][14]. The research team affirmed to certain ethical practices that will be observed in the study participants identity and personal details will not be disclosed and any data collected in the study will be kept confidential Participants were assured that informed consent will be sought and the well being of their children will be put into consideration. The sessions were meant to make parents support their children to participate in the study and through complete information and addressing any of the concerns that was provided during the session on engagement, the research team highlighted potential benefits to be gained through participation, including the contribution towards the valuable research and knowledge towards best practice.

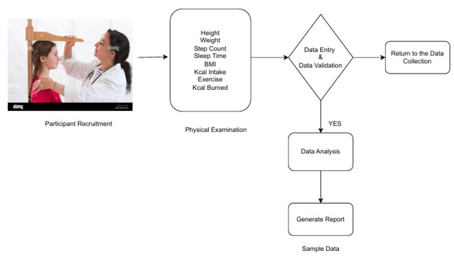

Fig. 1: Fig:1 hypothesized as Daily Health Metrics Framework, where in, participants were asked to collect and report different health measurements like height, weight, BMI, steps taken daily, amount of sleep, energy intake, physical activity and energy burnt on the daily basis[8][14].

2.2 Preprocessing

Preprocessing of data is a very important stage in developing models of machine learning, especially in the case of obesity. Outlier detection and treatment Outlier removal Data cleaning and formatting Handling missing values ,Data transformation and reduction Handling class imbalance Foot note SMOTE. 1. Outlier Detection and Handling: Outlier quality control of analysis and treatment is a process of analyzing the data in an attempt to identify and handle with the data point regarded as anomalous. In this case obesity indeed presents extreme circumstances where either the BMI value is very high or excessively low and this is likely to affect some normalization problems or mean shifts if one is not careful. 2. Data Cleaning and Formatting:In obesity datasets there are several steps involved in the data cleaning and formatting to reduce the chances of having inaccurate data. The second step in handling the data involves rounding off raw errors, converting standard units for instance height from centimeters to meters and weight from grams to kilograms For categorical data for instance activity levels, proper identification and encoding of the categorical data into numerical form. They also smooth out such inconsistencies as the date can be written in different formats and similar to this there can be typographical errors. Operations, such as mean imputation, replace missing values, while scaling methodologies, including normalization and standardization, guarantee each featureвЂ™s contribution to the analysis. 3. Handling Missing Values Using Mean Imputation: One of the ways of handling with missing data is what is known as mean imputation of missing values whereby missing data points are replaced with the mean of the data available in the same feature. Slightly different, mean imputation handles it by supplementing inapt information using average of similar kind of data, all in a bid to maintain datasetвЂ™s reliability. This can be easily managed using simpleimputer class from the scikit learn python library . 4. Time Series Data Formatting: The reason why time series data is useful in obesity prediction is because it arranges the health data including weight, energy intake and energy expenditure of the human body in equal periods of time [12]. Pandas are used for such operations where the data is to be resampled or structured while the process of mean imputation means replacing the missing values with the mean in order to maintain a continuous sequence. 5. Feature Engineering: In obesity research, feature engineering revolves around modification and construction of features that will enhance the effectiveness of the models of machine learning. For instance, instead of just using weight and height, Body Mass Index BMI, has a number of classes, such as underweight, normal weight, overweight, obese, which can provide relevant information for the model. Besides, new variables such as вЂњcaloric balance,вЂ™ which is a combination of physical activity and taking of calories can also be developed.

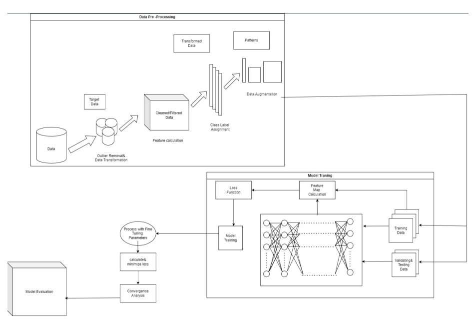

Fig. 2: Over all preprocessing framework for obesity prediction for adolescents

Data Aggregation In obesity related studies, data aggregation involves the processes of taking large datasets and summing them up in an intelligible manner using functions such as average daily calories taken or average activity per week or month. This process employs mean, median and sum among other algorithms to filter out short term volatility that is irrelevant in health predictions while upticking long term patterns. Missing values are usually handled by techniques like mean imputation so as to enhance the status of the obtained aggregated data.

3 Comparison Model

Naive Bayes Classifier (NB): A probability model based on the formulation of Bayes theorem in the assumption of the independency of the feature types. Can successfully be used with large datasets and feature spaces containing a high number of dimensions. It supposes features are independent in spite of the fact that it can markedly deviate from actual conditions in case of obesity-related data. Regularized Linear Discriminant Analysis (RLDA : An algorithm that performs a linear transformation of features in order to distinguish two or more classes to the highest extent possible. Random Forest (RF) : It is a type of learning algorithm which builds several decision trees and then combines them to take final decision. Is capable of handling large numbers of features and is not affected by the over fitting hence suitable for obesity dataset. Beneficial for problems with an unequal distribution of classes which is often occurs at obesity prediction when some classes can contain more instances than others (for instance normal weight vs obese). Decision Tree (DT): a decision tree that has inputs of features and the outcomes are classifications for features values. The regression models can be applied for both metric and non-metric variables, which gives it a wide applicability in analysis of obesity-related characteristics (including demographic or lifestyle). It can be noisy sensitive which means that it will develop high variance if the training data is intricate. Support Vector Machine (SVM): A technique of machine learning which finds the best hyperplane for categorizing the different classes in the feature space. Most useful when working with large sets of parameters, which can number tens or hundreds of characteristics referring to the lifestyle of the patient, his genetics, or environment, for example. Was found to be even more sensitive to the tuning of the free parameters especially when non-linear kernels are used.

Table 2: Comparative Analysis of Obesity Prediction Performance in Boys and Girls

Performance Metric	Boys	Girls
Accuracy	0.9520	0.9363
F1-Score	0.9618	0.9455
Precision (Increase)	0.9471	0.9323
Precision (Maintenance)	0.9275	0.9165
Precision (Decrease)	0.9445	0.9203
Highest Model Performance	SVM (0.9625)	LSTM (0.9575)
Statistical Significance (p-value)	<0.001	<0.001
Peak Performance Day	164th Day (0.9712)	137th Day (0.9549)

Long Short-Term Memory (LSTM) : One of the architectures of the RNN which aimed at performing well for the long-term dependencies in sequential data. Prescriptive for sequential data and therefore appropriate for time-series data where obesity related metrics had had changes recorded over time such as weigh-ins, dietary preferences. In order to capture long-term dependencies, a rather large number of data has to be used.

4 Obesity Prediction Analysis

One must first check the normality of the data using the Shapiro-Wilk test for which data should have a normal distribution for later statistical tests to hold. Levenes test should be used to check on the homoscedasticity which is

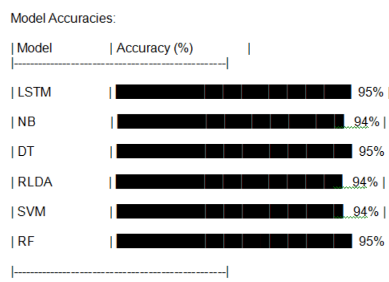

Fig. 3: comparisons of classification accuracy per models

important in ascertaining that the variances are equal in the groups to justify the use of parametric tests. This kind of test is a paired t-test that can be used in comparing the results of two or more machine learning models and thus, identify whether or not there is statistical significant in the performance of such models. Measures of accuracy, precision, recall, and the F1-score should be computed to determine the models capacity to estimate the rates of obesity with statistical significance to confirm the results. This will provide a more structured form of research, thus increasing the reliability and credibility of the results, and greatly help into improving the understanding of the methodologies towards the prediction of obesity rates.

5 Comprehensive Evaluation and metrics

Other important measures include accuracy which, measures the ratio of correctly classified instances out of all the instances predicted by the model, thus giving a general indicator of the models performance.The F1-score, which combines precision and recall into a single value, is also preferable where we have an unequal number of instances belonging to different classes. Further, different models can be compared, for instance, using the paired t-tests that allow for a hypothesis testing and checks of whether the difference observed in two metrics is statistically significant. Altogether, those indicators constitute an integrated approach for evaluating the models performance regarding the prediction of obesity and for identifying better development practices.

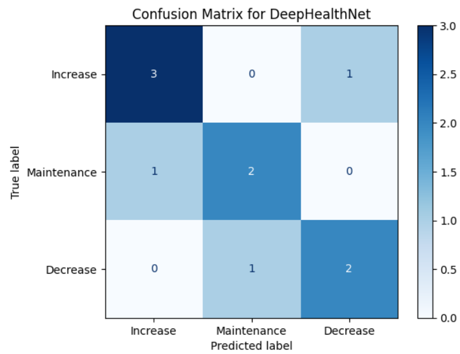

Fig. 4: confusion matrix of each class(Increase, Maintenance ,Decrease)

Accuracy: This metric means the final accuracy of the model concerning the classification of the instances. It is calculated as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

where TP = True Positives, is the sum of the correctly predicted positive observations, TN = True Negatives, is the sum of the correctly predicted negative observations, FP = False Positives, is the total of the wrongly predicted positive observations and FN = False Negatives, is the total of the wrongly predicted negative observations.

F1-Score: The second measure is the F1-score; this measure is preferred when dealing with the situation of class imbalance as it balances precision and recall rates. It is calculated using the harmonic mean of precision and recall:

$$F_1 = 2 \times \frac{(\text{PrecisionRecall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

6 Result

DeepHealthNet is a deep learning system solely developed to forecast obesity level in adolescents. Covariate 0.9631 which confirmed its efficiency for the prediction of obesity levels in the population.

Accuracy: The results presented for DeepHealthNet show that its average correctness reaches 0. 9437 whereas Long Short-Term Memory (LSTM) model achieved 0. Thus, Logistic Regression got an accuracy of 0.9448 and Support Vector Machine (SVM) got 0. 9446.

F1-Score: For DeepHealthNet F1-score was equal to 0. Models 9697 was moderate as it had a high value for accuracy demonstrating a good meld of precision and recollection while other models were lower reliability of their predictions.

Gender-Specific Performance: When tested according to the gender aspect DeepHealthNet recorded 0. 9561 in boys and none in girls; 9423 for girls, which shows that this model work well with various gender.

Table 3: Comparative Analysis of DeepHealthNet and Other Models for Obesity Prediction

Category	Detail	DeepHealthNet	Comparison
Input Indicators	Height, Weight, Waist Circumference, Calorie Intake, Physical Activity Levels	Used extensively	Core features used to predict obesity levels in adolescents.
Overall Performance	Accuracy	0.9437	Higher than other models listed below.
	F1-Score	0.9697	Demonstrates a balance between precision and recall.
	Statistical Significance	$p < 0.001$	Indicates results are highly reliable.
Gender-Specific Performance	Boys	0.9561	Shows effective performance in predicting obesity among male adolescents.
	Girls	0.9423	Indicates slightly lower but strong performance in predicting obesity among female adolescents.
Comparison with Other Models	LSTM	Not specified	Lower accuracy than DeepHealthNet.
	RLDA	0.9448	Slightly higher than DeepHealthNet but less robust in other metrics.
	Support Vector Machine (SVM)	0.9446	Very close to Logistic Regression but slightly behind in overall reliability.

7 Conclusion

The study identified some limitations among them being the use of only a particular age group and more importantly, the need to carry out studies in order to determine the validity of the model in other different populations and datasets. Because detailed health information is used and the modeling approach is strong, the framework provides a basis for early prevention and treatment of obesity Although other variables contributing to obesity have not been investigated, integration of more variables, like SES and diets, has cost potential for effective prediction.

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