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ANN-Powered Lifestyle Risk Prediction in Tech Industry Professionals

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***Abstract*—Stress and obesity are the most prevalent lifestyle-related health issues that significantly negatively impact a person's physical and mental health and often lead to chronic illnesses such as diabetes, anxiety disorders, and cardiovascular diseases. Obesity is characterized by high accumulation of body fat, which in turn increases the chances of metabolic syndromes, whereas stress, especially chronic stress, has been associated with physiological effects such as inflammation and immunological dysfunction, in addition to mental health problems. This paper investigates the possibility of using deep learning to predict the level of stress and obesity of an individual in a high-stress workplace setting, especially among IT workers. We applied Artificial Neural Network (ANN) to classify health risk levels based on two datasets emphasizing lifestyle characteristics associated with stress and obesity. We have used the SoftMax layer for multi-class classification and dense layers with ReLU activation for feature extraction. Our ANN models include the stress model and the obesity model with high prediction accuracy. Our deep learning approach provides a proactive answer for the management of such lifestyle diseases by accurately forecasting the risk levels and developing customized recommendations for lifestyle interventions. Thus, therefore indicates a potential for the assimilation of predictive analytics within the workplace wellness initiatives.**

***Index Terms*—Metabolic Syndromes, Multi-Class Classification, ReLU Activation, Artificial Neural Network, Lifestyle Interventions, Health Management, Physiological Effects, Inflammation, Immunological Dysfunction, Customized Recommendations.**

I. INTRODUCTION

As The tech sector has grown to be a vital component of the world economy, propelling innovation and influencing the digital era. However, professionals in this field face significant health difficulties due to the rigorous nature of their jobs. The prevalence of lifestyle-related diseases has increased because of the particular occupational risks associated with the technology sector, such as extended screen time, long hours of sedentary work, and elevated stress levels. There is a pressing need for focused preventative efforts because conditions including obesity, diabetes, cardiovascular illnesses, and mental health problems are becoming more common among those in high-tech jobs. with prompt interventions and lifestyle changes, lifestyle diseases which usually result from long-term behaviors and environmental factors can be avoided. However, because these health conditions are complicated, traditional methods of assessment frequently fail to capture the intricate relationships

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between different risk factors. Artificial Neural Networks (ANNs) provide a sophisticated and effective method for assessing these multifaceted health hazards because of their ability to analyze enormous volumes of data and simulate non-linear correlations. ANNs are a tempting option for lifestyle disease prediction because they may be used to identify complex patterns that are frequently difficult to detect using traditional statistical methods.

In this study, we create and apply an ANN-based model to forecast health risks associated with lifestyle choices among individuals in the tech sector. To create a customized health risk profile, this approach takes into account a wide range of behavioral, occupational, and environmental factors, including sleep patterns, work stress, food choices, and physical activity levels. The ANN model seeks to present a comprehensive picture of each person's health risk by examining these various inputs, identifying individuals who are more likely to develop lifestyle diseases. In doing so, it can act as a basis for customized interventions that are suitable to the requirements of tech workers, such as food advice, stress-reduction methods, or exercise regimens.

This study's importance goes beyond evaluating personal risk. The model's insights could guide workplace wellness activities in the tech sector, allowing companies to create programs that proactively address frequent health concerns among staff members. Businesses may increase overall job satisfaction, decrease absenteeism, and boost productivity by putting employee well-being first and encouraging better lifestyle choices. Furthermore, a wider framework for addressing lifestyle-related health hazards across industries can be created by adapting the ANN-powered strategy shown in this study to tech occupational situations.

A. Related Work

The suggested model is a predictive framework based on Artificial Neural Networks (ANN) that is intended to evaluate lifestyle-related health concerns, particularly for individuals in the IT sector. To produce a thorough risk assessment, this model incorporates a variety of lifestyle and health characteristics, including demographic data, dietary practices, work related stress, sleep quality, and physical activity levels. Preprocessing techniques like data cleaning, normalization, and feature selection are used to optimize the neural network's inputs after data gathering. Input, hidden, and output layers make up the ANN architecture, which allows the model to capture intricate, non-linear correlations between risk factors. The algorithm learns to precisely forecast each person's health risk score through repeated training and validation. Professionals are then empowered to adopt healthier lifestyle choices and reduce their chance of developing diseases like diabetes and obesity by using these ratings to provide individualized suggestions. The goal of this strategy is to support preventive healthcare and foster well-being in a high-stress work environment by customizing risk assessments to the unique problems of the tech sector.

A. Problem Statement

Technology workers' high rates of stress and obesity have become a serious health concern due to their sedentary work surroundings, erratic hours, and demanding jobs. Obesity and chronic stress are largely caused by unhealthy lifestyle choices including poor eating, inactivity, and sleep deprivation, which are frequently brought on by these variables. Even though these problems are becoming more well recognized, there are currently few accurate prediction methods that use physiological, occupational, and lifestyle data to identify people who are at risk. In order to reduce related health concerns, this study intends to use deep learning techniques to predict obesity and stress in IT professionals. This will allow for early intervention and tailored suggestions. Through filling this gap, the study aims to enhance the productivity and wellbeing of this essential workforce.

II. METHODOLOGY AND SOLUTION APPROACH

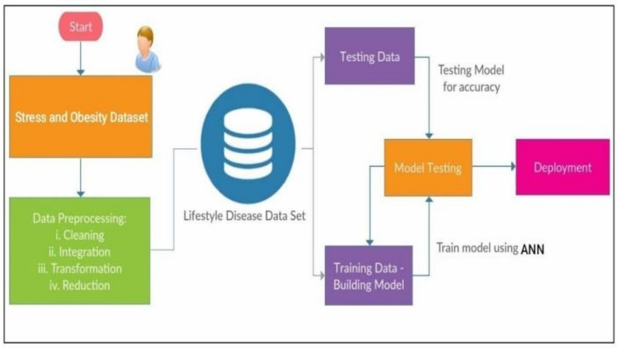

Figure 1. Flow Chart on Methodology

This model is a kind of artificial neural network made to evaluate intricate lifestyle data and forecast health hazards for workers in the IT sector. Because ANNs are better at capturing non-linear correlations than standard models, they can analyse a variety of inputs, including stress levels, physical activity, food, and sleep quality, all of which are critical for precise lifestyle risk prediction.

A. Model Architecture

The model consists of an input layer, several hidden layers, and an output layer. The input layer takes in various lifestyle and demographic features, while the hidden layers capture interactions and patterns between these features. Each hidden layer is fully connected, allowing the network to progressively learn more complex representations of the input data. The output layer produces a risk score indicating the likelihood of developing lifestyle-related health conditions.

B. Input

The model in this study is fed demographic and lifestyle information unique to people in the tech sector. A variety of variables that capture important lifestyle elements are included in the input features, including demographic information like age, gender, and job role, as well as physical activity level, eating habits, sleep quality, and stress connected to work. Self-reported health indicators and body mass index (BMI) are examples of additional elements. The input shape is specified to match the total number of selected features in the dataset in order to ensure compatibility with the ANN architecture. This enables the model to process each factor efficiently and capture the intricate interconnections impacting health risks associated to lifestyle.

C. Data Preprocessing and Scaling

This study is fed demographic and lifestyle information unique to people in the tech sector. A variety of variables that capture important lifestyle elements are included in the input features, including demographic information like age, gender, and job role, as well as physical activity level, eating habits, sleep quality, and stress connected to work. Selfreported health indicators and body mass index (BMI) are examples of additional elements. The input shape is specified to match the total number of selected features in the dataset in order to ensure compatibility with the ANN architecture. This enables the model to process each factor efficiently and capture the intricate interconnections impacting health risks associated to lifestyle.

D. Training the ANN Model

The architecture of fully linked networks is used to train the ANN model for lifestyle risk prediction. The selection of ANN was based on its capacity to capture intricate, non-linear correlations between health, demographic, and lifestyle characteristics. Each hidden layer in the model learns and transforms patterns in the scaled dataset to capture connections between health risk and lifestyle factors. The hidden layers use Rectified Linear Unit (ReLU) activation functions to introduce non-linearity, allowing the model to learn intricate patterns in the dataset. Dropout is applied to prevent overfitting by randomly disabling nodes during training, while batch normalization ensures that the learning process remains stable and efficient by normalizing layer inputs. Backpropagation is used during training throughout several epochs, with weights in each layer being adjusted to increase prediction accuracy. To avoid overfitting and stabilize the learning process, dropout and batch normalization techniques are used, which improves the model's ability to produce trustworthy risk evaluations for experts in the IT sector.

E. Predictions for Obesity and Stress

After training, the ANN model independently predicts the risk of obesity and stress for tech industry professionals based on their lifestyle and demographic inputs. The output for obesity risk is derived from features related to physical activity, dietary habits, BMI, and sleep quality, which collectively indicate factors influencing weight gain and metabolic health. Meanwhile, the output for stress risk is generated from work-related stress levels, sleep patterns, and other relevant lifestyle factors in the dataset. The model provides continuous predictions, assessing an individual's risk of obesity and stress under various lifestyle conditions, allowing for timely health insights and targeted intervention recommendations based on the predicted risks.

F. Model Evaluation

MSE (MSE (Mean Square Error)

The Mean Squared Error (MSE) metric measures the average of the squared variances between the estimated and actual values. A lower mean square error (MSE) in noise pollution prediction models indicates a higher level of accuracy, as the model's predictions closely align with the actual values.

R-SQUARE

The R-squared (R2) value measures the extent to which the independent variable(s) in a regression model explain the variance in the dependent variable. It is also referred to as the coefficient of determination. In noise pollution prediction models, a higher R-squared value indicates a stronger agreement between the model and the observed data, suggesting a higher level of correlation between the variables under study.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad \text{R}^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Where: y_i - true values of y
$\hat{y}_i$ - predicted values of y
$\bar{y}$ - average value of y

TABLE I: MODEL EVALUATION

Health Problem	Model	MSE	R2	Accuracy (%)
Obesity	Artificial Neural Network	1.45	0.90	97.75
Stress	Artificial Neural Network	2.18	0.88	95.56

G. Results

For model training, epochs are essential since they represent a single pass over the training dataset. Increasing the number of epochs generally helps the model learn more effectively, improving its predictions as it back propagates the weight adjustments. To prevent overfitting and guarantee that the model adapts adequately to new inputs, the ideal number of epochs must be selected. It is possible to ascertain when the model has achieved adequate learning by tracking the MSE throughout epochs.

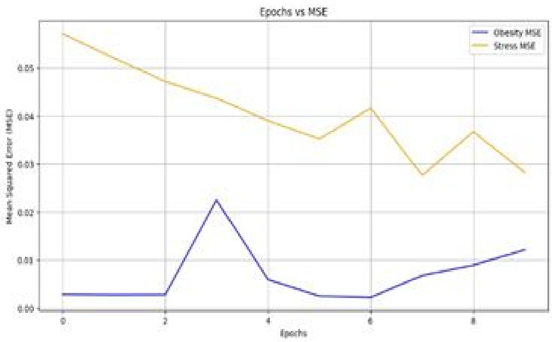

Figure 2. Graph between MSE and Epochs

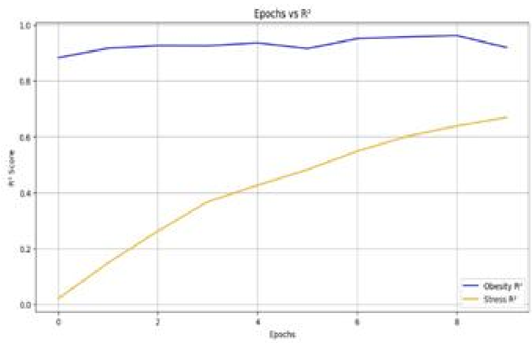

Figure 3. Graph between $R2$ score and Epochs

When evaluating the quality of a model, the correlation between epochs and $R2$ is also crucial. As the model considers the variance in the data, the $R2$ value usually gets better in the early epochs. In general, $R2$ stabilizes and, ideally, reaches a maximum point as the epochs increase. The model explains most of the variance without over fitting when the $R2$ value is high at the ideal number of epochs. Overfitting may be indicated, though, if $R2$ begins to decrease as the number of epochs increases. Therefore, balancing epochs in terms of MSE and $R2$ can aid in creating a strong model that accurately forecasts stress and obesity levels across a range of data.

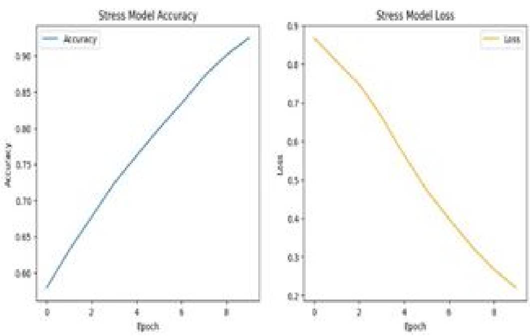

Figure 4. Graphs on Stress Model's Accuracy and Loss

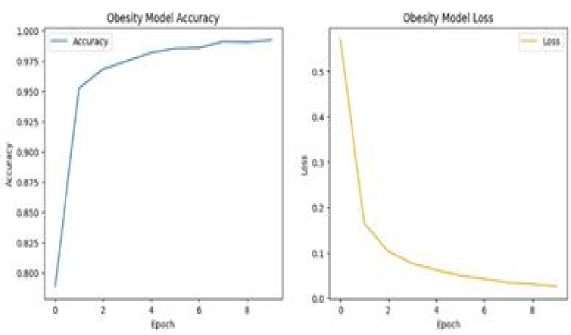

Figure 5. Graphs on Obesity Model's Accuracy and Loss

Accuracy, MSE, and $R2$ all improved over time as the model in this study was trained over a number of epochs. The model's capacity to generate dependable classifications that closely match real-world results was validated by comparing predictions with actual data. The model's predicted accuracy is ensured without overfitting thanks to this ongoing assessment and metrics like $R2$ and MSE, which allow for a fine-tuning procedure for the number of epochs. Actionable insights on obesity and stress risk are provided by the output, which is backed by trustworthy accuracy measures that confirm the model's effectiveness.

III. CONCLUSIONS

In today's world, when lifestyle-related health problems are becoming more common, these prediction models are essential for encouraging tech workers to take an active approach to their health. Organisations can use artificial neural networks to develop health programs and interventions that are specifically suited to the needs of their employees. This strategy improves overall productivity and job satisfaction in addition to creating a healthier work environment. In the end, the effective application of these predictive technologies can help address the issues brought on by contemporary work lives and foster a more knowledgeable and health-conscious culture within the tech sector. The findings of the ANN-powered lifestyle risk prediction model for professionals in the IT sector provide important latest information on the health hazards that are common in this group. The model's remarkable accuracy of 97.75% for predicting obesity and 95.56% for predicting stress indicates how well it can detect important lifestyle factors that lead to these health problems. The model's robustness is further highlighted by its combined accuracy of 96.65%, which suggests that it has the potential to be a trustworthy tool for evaluating lifestyle risks in the tech sector. This high degree of accuracy indicates that the model can manage and analyse complex datasets efficiently, which can help identify health hazards related to high-stress job demands and sedentary work settings early on.

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