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Review Article

Application of Machine Learning Algorithm and Artificial Intelligence in Improving Metabolic Syndrome related complications: A review

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Abstract

Aim: This review provides a concise summary of the utilisation of artificial intelligence (AI) in the context of metabolic diseases and their impact on overall well-being. The primary emphasis is placed on exploring the potential applications and addressing the issues associated with employing AI-based methodologies for both research purposes and clinical treatment in the context of non-communicable diseases. **Methods:** The relevant published publications were summarised by conducting computerised literature searches on several reputable databases using specific keywords such as MS, Artificial Intelligence (AI), Machine Learning (ML), Coronary Heart Disease, Obesity, and dyslipidemia. The researchers picked papers that had unique data and integrated the significant findings from these studies into the conclusion, which pertains to the present state of Metabolic Syndrome. **Results:** In summary, although the utilisation of artificial intelligence in educational interventions shows potential, it is important to acknowledge its inherent limits. Although there is a growing body of literature on the utilisation of digital and intelligent tools in the management of MS, a significant proportion of relevant studies suffer from limitations such as insufficient sample sizes or a failure to establish the clinical significance of the tested interventions. Notwithstanding these challenges, the advancements in utilising artificial intelligence (AI) in the field of medicine have been rapidly evolving, and it is imperative to acknowledge the potential and scholarly significance of these applications. **Conclusion:** The integration and comprehensive utilisation of certain artificial intelligence (AI) technologies can enable future health education on MS to provide comprehensive, personalised, and intelligent training. This intervention will provide patients with enduring protection and ongoing guidance throughout their lives.

Keywords: *Artificial Intelligence, Machine learning, Metabolic Syndrome*

Introduction

The integration of artificial intelligence (AI) has become pervasive throughout several domains of human society, encompassing AI-driven services and occupations, some of which have been shown to exert a notable adverse impact on individuals, such as within the healthcare sector. In light of the escalating health needs, particularly among the elderly population, it is imperative to develop alternative strategies that optimise and enhance existing healthcare resources in response to the prevailing staffing shortages within the global health and social system. Extensive research is currently being conducted to explore the application of AI in various aspects of healthcare, including prevention, diagnosis, innovative drug development, and post-treatment support. These investigations have the potential to bring about significant transformations in the entire patient experience. However, it is important to note that AI is predominantly employed in the treatment of cardiovascular, neurological (such as Parkinson's disease and stroke), and cancer ailments (Jiang, *et al.*, 2017). While the aforementioned technology improvements provide assistance to individuals across all age

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groups, it is important to acknowledge that different age cohorts may exhibit distinct health considerations.MS, sometimes referred to as "insulin resistance syndrome," "syndrome X," "hypertriglyceridemia waist," and "the deadly quartet," is becoming recognised as a substantial risk factor for cardiovascular disease. The initial universally recognised definition of MS was formulated in 1998 by the diabetic consulting group of the World Health Organisation (Grundy *et al.*, 2004).MS is defined as the coexistence of at least two of the following risk factors: obesity, shown by waist-hip ratio or body mass index; hyperlipidemia, characterised by hypertriglyceridemia and low levels of high-density lipoprotein (HDL) cholesterol; hypertension; or microalkaline urea. Furthermore, the authors provided a definition of MS that encompasses the manifestation of insulin resistance, including impaired fasting glucose, impaired glucose tolerance, or type 2 diabetes mellitus. Multiple iterations of this concept have been proposed since the initial description of MS.The global distribution of MS exhibits variability, often exhibiting a correlation with the incidence of obesity. There exists a notable variation in prevalence when considering parameters such as age, gender, race/ethnicity, and diagnostic criteria. Approximately 25% of individuals residing in Europe and a minimum of 20% of Americans are afflicted by MS. Despite the comparatively lower frequency of MS in South-east Asia, the region is rapidly approaching the rates observed in Western countries. According to the findings of Beltrán-Sánchez and colleagues, the age-adjusted prevalence of MS in the United States had a decline from 25% in 2000 to 22.9% throughout the period between 1999/2000 and 2009/2010, as indicated by data obtained from the National Health and Nutrition Examination Survey (NHANES) (Beltrán-Sánchez, *et al.*, 2013). Moreover, there exist variations in MS that are influenced by factors such as race and gender. Ford *et al*. (2002) utilised NHANES data collected from 1988 to 1994 to elucidate the prevalence of MS components in the United States, with a focus on gender and race.MS has a higher prevalence among African American women, with a 57% increased likelihood compared to African-American men. Similarly, Hispanic women have a 26% higher incidence of MS compared to Hispanic men. According to the cited source, it has been shown that individuals of Hispanic descent are more likely to have insulin resistance, whereas hypertension is more widespread among African Americans. On the other hand, dyslipidemia appears to be more common among those of White ethnicity (Grundy, et al.,2008). According to a recent study conducted by Miller *et al.*(2014) was shown that 10.1% of the teenage population in the United States had MS. It was shown that individuals of Hispanic descent exhibit a heightened susceptibility to Metabolic Syndrome, whereas males exhibit a greater likelihood of developing the condition compared to females. MS is associated with an increased risk of both atherosclerotic and non-atherosclerotic cardiovascular disease (CVD). The question of whether risk arises from the cumulative effect of its individual components or from the clustering of these components leading to a synergistic hazard remains a subject of ongoing debate. Based on the most recent meta-analysis conducted by Motillo *et al.*(2010) it has been shown that individuals with MS face a twofold increase in the risk of cardiovascular disease (CVD) events, as well as a 1.5-fold elevation in all-cause mortality.MS is effectively controlled by the implementation of a dual approach that integrates pharmacological treatments and lifestyle modifications, with the ultimate goal of mitigating the risk of cardiovascular disease (CVD).

In order to enhance the understanding of the current clinical state, such as determining the risk score for heart disease or to predict future outcomes, such as daily mood fluctuations (Atkins, *etal*., 2019), AI utilises large multimodal datasets to identify patterns. These datasets encompass information from both individual cases and collective data across several individuals (Wiens & Shenoy, 2018). The significance and use of this particular technology are more prominent within the ongoing digital healthcare revolution. Technological improvements, such as the widespread use of smart phones, wearables, embedded sensors, and the introduction of enormous databases like electronic health records, have brought about significant changes in the clinical care and research environment. AI technologies provide the capability to dynamically assess complex data and generate valuable insights, therefore augmenting treatment processes and improving outcomes. The use of personalised predictions in clinical decision-making has the capacity to significantly transform metabolic healthcare and research, thanks to the acquisition and application of AI techniques. In a more precise manner, AI has the potential to aid in the proactive and impartial evaluation of health complaints, therefore facilitating the diagnosis and administration of therapy that is customised to meet the unique requirements of individual patients. This includes the provision of long-term monitoring and the management of care. The primary potential of AI in the field of metabolic disease-related healthcare and research lies in its reliance on extensive data. This reliance enables AI to effectively enhance understanding of the most effective interventions for specific individuals and the optimal timing for their implementation. Nevertheless, a significant portion of this progress is propelled by individuals specialised in machine learning, such as data scientists, computer scientists, and engineers. However, there is a potential concern that this advancement may get detached from practical considerations in the field of clinical practise. This article presents the viewpoints of clinician-scientists about the subject of expertise in AI and data science. This review provides a concise summary of the utilisation of AI in the context of metabolic diseases and their impact on overall well-being. The primary emphasis is placed on exploring the potential applications and addressing the issues associated with employing AI-based methodologies for both research and clinical treatment in the context of non-communicable diseases.

Methodology:

Relevant published publications were gathered by using the following keywords in automated literature searches of numerous trustworthy databases: MS, AI, ML, OCHD, obesity, dyslipidemia, and artificial intelligence (AI). Taking into consideration their important discoveries, a conclusion regarding the current state of MS was combined with a subset of prospective studies using original data (Figure 1).

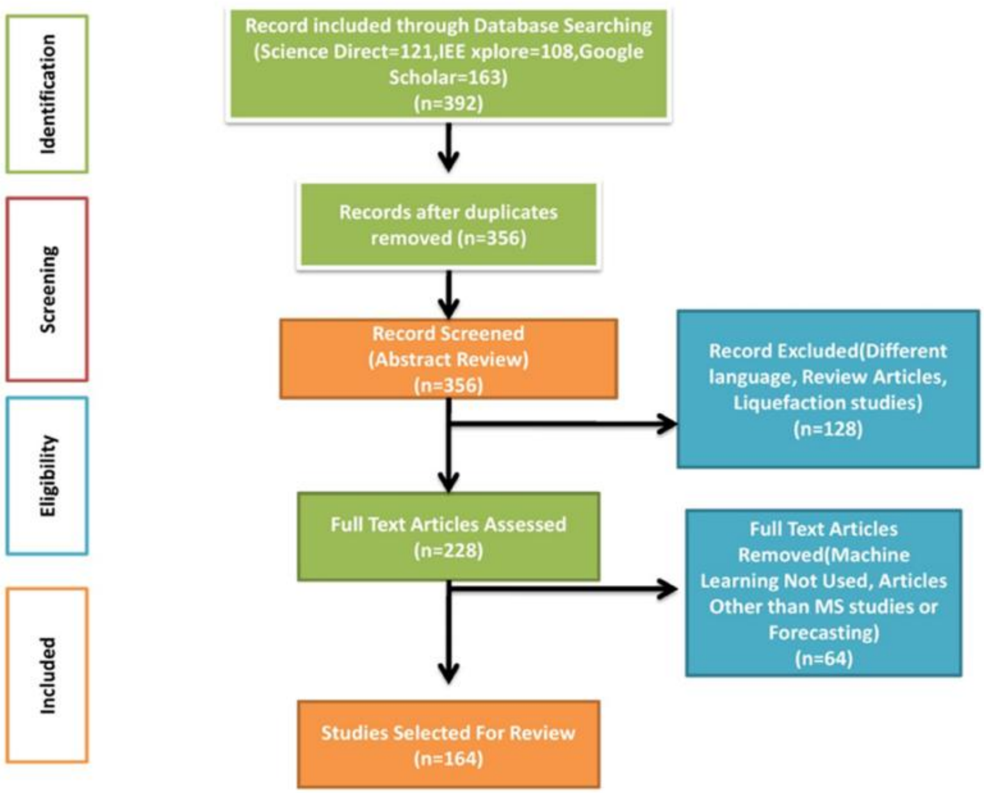

Figure 1: Prisma Diagram of the selection process of the research articles of this review.[The search string used in this study is-("Neural Network" or "Machine Learning" or "SVM" or "RNN" or "HMM" or "Hidden Markov" or "Fuzzy" or "Deep Learning" or "Data Mining" or "SVR" or "PNN" or "LSTM" or "Clustering" or "Radial Basis" or "RBF" or "Support Vector") and ("Metabolic Syndrome") and ("Prediction"). Based on this search string, we have initially found 392 research articles from Science Direct, Google Scholar, and IEEE Xplore digital library. After screening and eligibility testing, we have selected 164 research papers for this review].

Discussion:

As was already noted, eating more calories than one needs for metabolism leads to the development of Metabolic Syndrome. Table 1 shows the various versions of this idea that have been put out since MS was first described. All the aforementioned criteria for metabolic syndrome continue to function as indicators of atherosclerotic cardiovascular disease.Managing underlying risk factors requires a change in lifestyle.Essential preventive and management techniques include weight loss and maintaining a healthy weight and proper health education (Rochlani, *et al.*, 2017).The objective of weight reduction is to reduce caloric consumption by 500–1000 calories per day while losing 7–10% of one's starting body weight over a period of 6–12 months. Other MS components can also be controlled by dietary changes; for instance, dyslipidemia, hyperglycaemia, and hypertension are known to be helped by a low consumption of saturated and trans fats, cholesterol, sodium, and simple carbohydrates. Diets with a high or very low-fat content aggravate atherogenic dyslipidemia; as a result, it's typically advised to consume 25–35% of daily calories as fat. Bariatric surgery can be beneficial when used wisely in excessively obese patients. Weight loss aids in the development of all aspects of exercise. Exercise boosts calorie intake, which promotes weight loss and lowers total CVD risk. Approximately 30 to 60 minutes of moderate intensity exercise per week, along with deliberate efforts to change a sedentary lifestyle, can be helpful for the management of MS (Rochlani, *et al.*, 2017).

Table1. Definitions of Metabolic Syndrome

Clinical assess	**WHO 1999 (**WHO, 2017**)**	**NCEP (National Cholesterol Education Program) ATP3 2001** (Expert Panel on Detection, E., 2001)	**IDF (International Diabetes Federation) 2005** (Alberti, *et al.*, 2005)	**American Association of Clinical Endocrinologist (AACE)** 2003 (Moghissi,*et al.*2009).	**EGIR: Group for the Study of Insulin Resistance 1999** (Balkau, B, 1999).
Criteria	Presence of insulin resistance or glucose along with any two or more of the following	Presence of any three or more of the following	Waist circumference parameters along with the presence of two or more of the following	High risk of insulin resistance◊ or BMI parameters or waist circumference parameters	Insulin resistance or fasting hyperinsulinemia (ie., in top 25% of the laboratory-specific reference range)
Obesity	BMI >30 kg/m^2	Waist > 102 cm (men) or >88 cm (women)	Waist > 94 cm (men) or >80 cm (women)	BMI ≥25 kg/m^2 or waist ≥102 cm (men) or ≥88 cm (women)	Waist ≥94 cm (men) or ≥80 cm (women)
Blood pressure	>140/90 mmHg	>130/85 mmHg or drug treatment for hypertension	>130/85 mmHg or drug treatment for hypertension	≥130/85 mmHg	≥140/90 mmHg or drug treatment for hypertension
Dyslipidaemia	HDL cholesterol <0.9 mmol/L (35 mg/dl) in men, <1.0 mmol/L (40 mg/dl) in women Triglycerides >1.7 mmol/L (150 mg/dl)	HDL cholesterol <1.0 mmol/L (40 mg/dl) in men, <1.3 mmol/L (50 mg/dl) in women or drug treatment for low HDL-C Blood triglycerides >1.7 mmol/L (150 mg/dl) or drug treatment for elevated triglycerides	HDL cholesterol <1.0 mmol/L (40 mg/dl) in men, <1.3 mmol/L (50 mg/dl) in women or drug treatment for low HDL-C Blood triglycerides >1.7 mmol/L (150 mg/dl) or drug treatment for elevated triglycerides	HDL cholesterol <1.0 mmol/L (40 mg/dL) (men); <1.3 mmol/L (50 mg/dL) (women) Blood Triglyceride ≥1.7 mmol/L (150 mg/dL)	HDL cholesterol <1.0 mmol/L (40 mg/dL) Triglycerides or ≥2.0 mmol/L (180 mg/dL) or drug treatment for dyslipidemia
Blood glucose	>6.1 mmol/L (110 mg/dl), 2 h glucose >7.8 mmol (140 mg/dl)	Blood glucose greater than 5.6 mmol/L (100 mg/dl) or drug treatment for elevated blood glucose	Blood glucose greater than 5.6 mmol/L (100 mg/dl) or diagnosed diabetes	Fasting glucose ≥6.1 mmol/L (110 mg/dL); ≥2-hour glucose 7.8 mmol/L (140 mg/dL)	Fasting glucose 6.1 to 6.9 mmol/L (110 to 125 mg/dL)

** BMI :Body Mass Index; HDL-C:High Density Lipoprotein Cholesterol; IFG: Impaired Fasting Glucose; IGT:Impaired Glucose Tolerance; IR:Insulin Resistance;T2DM:Type2 Diabetes Mellitus; TG:Triglycerides; WC:Waist Circumference

Pharmacotherapy:

In addition to mitigating the underlying risk factors, pharmacotherapy is an additional approach for the prevention of cardiovascular disease (CVD). Significant pharmacological interventions encompass the utilisation of statins to address dyslipidemia, antiplatelet medicines to mitigate prothrombotic risk, and insulin sensitizers to avoid the onset of diabetes. Given the current absence of a singular therapeutic intervention for MS, individuals diagnosed with this condition are required to undergo prolonged treatment regimens involving many medications. However, this poses challenges for patients due to the complexity of managing multiple drugs simultaneously, a phenomenon known as polypharmacy, and the resulting low adherence rates. Hence, notwithstanding the lack of knowledge about the potential impact of naturally occurring substances on extended cardiovascular outcomes and adherence throughout time, there is an increasing inclination to use them as a means to mitigate the danger and advancement of MS. Therefore, the implementation of appropriate dietary therapy is increasingly recognised as a critical component in the treatment of Metabolic Syndrome (Rochlani, *et al.*, 2017).

The Concept of AI and its benefits:

Artificial intelligence is a multidisciplinary concept that draws upon several theoretical foundations, including computer science, control theory, information theory, neuropsychology, philosophy, and linguistics (Russell & Norvig, 2016). AI often employs synthetic methods to imbue computers with cognitive capabilities. The term "artificial intelligence" was initially coined in the year 1956. The notion was further developed and several theories and technologies were offered in subsequent research, aiming to enhance computer-based human intelligence. There is a prevailing belief that AI has the potential to alleviate individuals from arduous cognitive and physical tasks through its ability to simulate and enhance human cognitive functions. The discipline of artificial intelligence, also referred to as machine intelligence, encompasses a wide range of areas and topics. The categorization of AI techniques in the context of diabetes-related applications may be delineated into three distinct groups, which are determined by their respective objectives. These divisions include the exploration and discovery of information, the acquisition of knowledge to effectively utilise information, and the derivation of logical inferences from the available information (Contreras & Vehi, 2018).The phrase "Knowledge Discovery in Databases" (KDD) refers to the process of developing and implementing algorithms that aim to uncover potential knowledge inside databases. The primary goal of Knowledge Discovery in Databases (KDD) is to identify useful and comprehensible information. This purpose necessitates a comprehensive and thorough grasp of the specific subject of study being investigated. The K-means method, K-nearest neighbours (KNN) algorithm, and hierarchical clustering technique are widely recognised as prominent technologies in research. In relation to the domain of knowledge acquisition, the objective is to enable autonomous machine learning, devoid of human interaction or assistance, hence enabling the machine to predict the future state of intricate systems and enhance decision-making. The approach encompasses numerous strategies that integrate inductive aspects, each possessing distinct advantages when used adaptively to different situations. Numerous techniques are frequently used in various disciplines, including artificial neural networks (ANNs), support vector machines (SVMs), random forest (RF) algorithms, evolutionary algorithms (EAs), deep learning (DL), naïve Bayes (NB), decision trees (DTs), and regression algorithms (RAs)(Li, *et al.*, 2020).Expert systems are commonly employed for the purpose of deriving conclusions from data inside the ultimate category. Knowledge acquisition interfaces, knowledge bases comprising rules and information, and inference engines are often recognised as the fundamental components of such systems. These systems employ the utilisation of information acquired from previous situations and the experience of professionals to understand concepts that are ambiguous and unclear, hence helping for decision-making in novel circumstances. In this subject, case-based reasoning (CBR), fuzzy logic (FL), and rule-based reasoning (RBR) are often employed approaches. Many approaches are frequently used in many disciplines, including artificial neural networks (ANNs), support vector machines (SVMs), random forest (RF) methods, evolutionary algorithms (EAs), deep learning (DL), naïve bayes (NB), decision trees (DTs), and regression algorithms (RAs). Expert systems are commonly employed to derive conclusions from data within the ultimate classification. Knowledge acquisition interfaces, knowledge bases comprising rules and information, and inference engines are often recognised as the fundamental components of such systems. These systems employ the information acquired from previous situations and the skills of professionals to comprehend vague concepts and ambiguity, providing assistance for decision-making in novel circumstances. The methodologies often utilised in this field include rule-based reasoning (RBR), case-based reasoning (CBR), and fuzzy logic (FL) (Li, *et al.*, 2020)

Application of AI in managing MS: discussion on recent development

Non-communicable diseases (NCDs) are the primary worldwide health challenges confronting the human population. According to the NCDs Global Status Report published by the World Health Organization, non-communicable diseases (NCDs) are responsible for the primary cause of death for around 41 million individuals globally on an annual basis. According to the cited source (WHO, 2018), it is reported that 71% of the total 57 million fatalities worldwide can be attributed to this phenomenon. In this particular case, non-communicable diseases (NCDs) are identified as the primary determinant of the annual occurrence of 15 million premature deaths among adults aged 30 to 70. The primary subcategories of non-communicable diseases (NCDs) are cardiovascular ailments, diabetes mellitus, malignancies, and chronic respiratory diseases. It is noteworthy that an estimated 17.9 million individuals succumb to cardiovascular disorders annually, with cancer being the cause of death for 9 million individuals, respiratory diseases for 3.9 million individuals, and diabetes for 1.6 million individuals (Forouzanfar, *et al.*, 2016). It is well recognized that modifiable risk factors such as inadequate dietary patterns, sedentary lifestyles, environmental influences, and the use of cigarettes and alcohol are associated with the development of obesity, hypertension, and increased levels of cholesterol. In contrast, non-modifiable risk factors including genetics, age, and sex (WHO, 2017,Kathirvel& Thakur 2018).Fortunately, the elimination of the primary risk factors might potentially lead to the avoidance of about 80% of cases of heart disease, stroke, and diabetes, as well as 40% of malignancies (Chen, *et al.*, 2018, WHO, 2012).The majority of non-communicable diseases (NCDs) are commonly diagnosed during advanced stages. Engaging in individual healthcare practices may help mitigate the chance of mortality if non-communicable diseases (NCDs) can be anticipated prior to their onset. Hence, it is imperative to construct a decision support system for the purpose of monitoring the progression of non-communicable diseases (NCDs) and identifying those at a heightened risk.

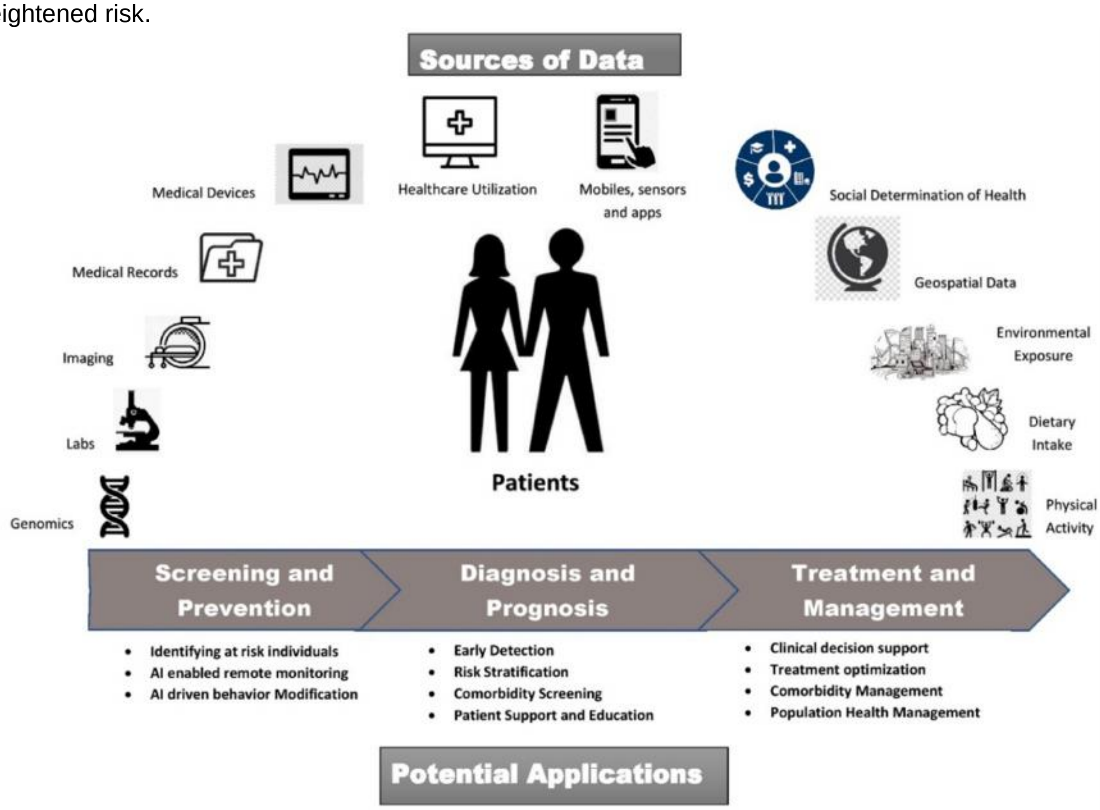

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Figure 2. Prediction of MS and its Management with the help of Artificial Intelligence

The utilization of artificial intelligence in the healthcare industry has shown a notable increase in recent times. Nevertheless, decision-making reactions are fraught with several concerns. In recent research, there has been a notable development of advanced methodologies that leverage data-driven approaches and machine learning techniques to effectively tackle the aforementioned difficulties (Davagdorj, *et al.*, 2019, Park, *et al.*2021, Ali, *et al.*2020, Panigrahi, *et al.*, 2021, El-Sappagh, *et al.*, 2021, Davagdorj, *et al.*, 2020, Carvalho, *et al.*, 2019) (see Figure 2). The absence of a sophisticated framework poses challenges for several systems in effectively handling datasets with high dimensions and determining the most relevant aspects to calculate a comprehensive weight for them (Davagdorj, *et al.*, 2019, Park, *et al.*2021, Ali, *et al.*2020). The work introduced a novel healthcare monitoring system that utilizes feature fusion and ensemble deep learning techniques for the prediction of heart disease (Ali, *et al.*2020). The authors employed the feature fusion approach to integrate the acquired characteristics derived from sensor data with electronic medical information. Subsequently, the elimination of redundant and superfluous features was carried out utilizing the features information gain technique. Additionally, the system performance was augmented by the use of the conditional probability approach, resulting in the generation of distinct feature weights for each class. In conclusion, a deep learning ensemble model was successfully trained to make predictions regarding heart disease, exhibiting superior performance in terms of accuracy when compared to earlier methodologies. Consequently, a significant portion of the existing work has focused on assessing the precision and rate of false positives shown by classification algorithms. The primary limitation in evaluating classifier performance should be the absence of other performance parameters, such as model construction time, misclassification rate, and accuracy (Panigrahi, *et al.*, 2021). Furthermore, the analysis of time-series data plays a vital role in the effective management of chronic diseases, enabling medical personnel to thoroughly evaluate a patient's historical health records in order to facilitate a comprehensive and progressive diagnosis. However, as a result of its exorbitant cost, especially in underdeveloped countries, data is generally limited or inaccessible for utilizations. The aforementioned characteristics encompassed patient comorbidities, cognitive assessments, prescription records, and demographic information. The results of their study demonstrated that the inclusion of comorbidity and medication variables, in conjunction with other factors, significantly enhanced the predictive capabilities of all models. The Random Forest (RF) model demonstrated the best projected accuracy. Ensemble methods and deep learning, akin to intricate models, exhibit enhanced efficacy in enhancing the identification and administration of diverse chronic ailments (Davagdorj, *et al.*, 2020). The bulk of existing research, however, offer limited reasons for their conclusions. In general, the best decision support system is characterized by two crucial requirements: explainability and accurate prediction performance (Carvalho, *et al.*, 2019). Accurate forecast performance during testing can contribute to the development of model confidence to a certain extent. Contemporary research studies commonly exhibit a shared limitation pertaining to their use of black-box models, despite their notable levels of predictive accuracy. Consequently, the implementation of predictions in real-world healthcare applications poses challenges, and the end-user remains uninformed about the underlying internal logic behind these forecasts. In many instances, medical professionals exhibit skepticism towards results derived from black-box models without explanatory capabilities (Carvalho, *et al.*, 2019,Lauritsen, *et al.*, 2020, Elshawi, *et al.*, 2019). In the context at hand, it is imperative to carefully choose an appropriate collection of features with the aim of excluding superfluous attributes that offer a range of advantages, including enhanced accuracy in learning outcomes as well as increased reading and comprehension abilities. The process of selecting a collection of relevant features remains challenging in healthcare applications. The information gain, gain ratio, and correlation coefficients feature selection strategies were proposed in numerical research. Nevertheless, the limitations of these algorithms lie in their inability to consider the interplay between characteristics, rendering them unsuitable for use in healthcare settings (Davagdorj, *et al.*, 2020). Furthermore, there exists a limited body of research that specifically examines the optimization of machine learning model parameters in order to improve overall performance. The Deep SHAP based deep neural network (DNN) with a feature selection technique to build an accurate and understandable decision assistance system will be beneficial in order to overcome the aforementioned issues. Another recent study conducted by Davagdorj and colleagues (2021). Three alternative sets of relevant features are created from the NHANES dataset for building decision support models of NCDs. This study builds a predictive and explainable decision support model of NCDs using data from the National Health and Nutrition Examination Survey (NHANES). Three parts make up the suggested framework. Elastic net (EN)-based embedded feature selection and data cleaning are used to create representative features in the first component. The DNN classifier is tweaked with the hyper-parameters in the second component and used to train the model with the chosen feature subset. The Deep SHAP technique offers two types of model explanations in the final component: (I) a population-based explanation of the risk factors that affected the model's forecast; and (II) a human-centered explanation of a particular incident. Consideration is given to the entire modelling process, including feature selection, training, hyper-parameter tweaking, model evaluation, and justifications.

Machine learning Techniques for MS and other Non-communicable Diseases:

Several research (Bang., *et al.*, 2019, Ge, *et al.*, 2020, Mohan, *et al.*, 2019, Xiao, *et al.*, 2019, Ijaz, *et al.*, 2020, Panigrahi, et al, 2021, Ali, *et al.*2021,Srinivasu, *et al.*, 2021, Davagdorj, *et al.*, 2021, Pinto, *et al.*, 2020, Fang, *et al.*, 2020, Batbaatar, et. al, 2020)have concentrated on enhancing the precision of NCD diagnosis models by the use of feature selection approaches and advanced machine learning classifiers. Bang *et al.*, (2019) have proposed the development of a predictive model for many diseases. This model would utilize meta-genome data obtained from a total of 1,079 individuals, comprising both healthy persons and patients diagnosed with one of six specific ailments. The authors employed forward selection and backward elimination techniques to construct prediction models utilizing Logit Boost, SVM, KNN, and logistic model tree classifiers. The LogitBoost classifier had the best level of accuracy, with a score of 98.1, when compared to the other four classifiers in the conducted tests. The researchers also suggested the optimal feature subsets identified by the process of backward elimination, namely at the genus level. In a similar vein, researchers conducted an investigation into a technique for predicting chronic illnesses using multi-label neural networks. This involved combining neural networks with multi-label learning technology, employing a cross entropy loss function and a backward propagation algorithm (Ge, *et al.*, 2020).In order to ascertain the various classifications of chronic diseases, a cohort of 19,773 individuals diagnosed with 10 distinct chronic diseases was utilized from the MIMIC-II database. The objective of the work conducted by the authors (Mohan, *et al.*, 2019) was to construct a predictive model for heart disease by employing feature selection techniques and several machine-learning algorithms, including Naive Bayes, generalized linear models, linear regression, deep learning, decision trees, random forests, gradient boosted trees, and support vector machines (SVM). The researchers utilized the cardiovascular disease dataset available from the UCI Machine Learning Repository, comprising a total of 303 patient records and encompassing 13 distinct variables. The experimental data demonstrate that the hybrid RF with a linear model prediction model for heart disease has enhanced performance, achieving an accuracy level of 88.7%. A previous study (Xiao, *et al.*, 2019) developed a prediction model for the course of chronic kidney disease, utilizing data obtained from the Department of Nephrology at Huadong Hospital and Shanghai Fudan University Affiliated Hospital. The authors conducted a comparative analysis of many machine learning classifiers, including LR, EN, LASSO, ridge, SVM, RF, KNN, NN, and XGBoost. Additionally, they investigated the importance of variable components within each prediction model. Based on the empirical results obtained from their studies, it was seen that EN, LASSO regression, ridge regression, and LR had the highest overall predictive capability, as evidenced by their average AUC and accuracy values above 0.87 and 0.80, respectively. The researchers addressed the challenges of outliers and class imbalance in order to construct a robust predictive model for early detection of cervical cancer (Ijaz, *et al.*, 2020). The researchers started their investigation by employing several methodologies for identifying outliers, such as the use of isolation forest and density-based spatial clustering of applications with noise. The issue of class imbalance was subsequently addressed by the utilizations of the synthetic minority over-sampling technique (SMOTE) and SMOTE with Tomek connection. A random forest (RF) classifier was utilized for the purpose of predicting cervical cancer. Panigrahi *et al*, (2021)examined a unified intrusion detection system that utilizes decision trees to address the challenges posed by unbalanced datasets in both binary and multiclass scenarios. The researchers introduced supervised relative random sampling as an enhanced variant of the random sampling technique. This method aims to provide a representative sample from a dataset that exhibits significant imbalances across its classes. The suggested approach is applied during the pre-processing phase of the detector. In order to achieve a balanced sample from a dataset that exhibits a large class imbalance, the researchers introduced a technique called supervised relative random sampling during the pre-processing step of the detector. This method is an enhanced version of the random sampling approach. The researchers used bidirectional long short-term memory (Bi-LSTM) models, ontologies, and data mining methodologies inside their proposed big data analytics framework. The Bi-LSTM classifier is employed for the purpose of forecasting hazardous medication responses and abnormal patient circumstances. In a separate investigation Davagdorj *et al.*, (2021) devised a computerized system aimed at categorizing skin ailments by employing MobileNet V2 and LSTM deep learning models. The dataset utilized in the study comprised more than 10,000 dermatoscopic photographs, which were collected from individuals residing in various geographical locations worldwide. The researchers devised a methodology that shown superior performance compared to several methodologies, such as convolutional neural networks, extremely deep convolutional networks for large-scale picture identification established by the visual geometry group, and fine-tuned neural networks. Additionally, it necessitated the minimal computational effort. The efficacy of wrapper, embedding, or hybrid feature-selection algorithms in selecting relevant feature subsets for non-communicable diseases (NCDs) has been demonstrated to surpass that of typical filtering processes (Davagdorj, *et al.*, 2021). Additionally, it is important to note that a significant number of researchers in previous studies endeavored to employ feature selection strategies in order to enhance accuracy and get a deeper comprehension of the aetiology of non-communicable diseases (NCDs). Based on previous research findings, it has been observed that deep neural networks (DNN), support vector machines (SVM), and ensemble classifiers exhibit superior performance in comparison to other baseline models (Fang, *et al.*, 2020, Batbaatar, *et. al*, 2020).

Application of Education and Management for MS and related conditions:

When compared to traditional educational approaches, AI-based education has many benefits, including reduced costs, simple implementation, broad coverage, flexible doctor-patient interaction, avoidance of repetitive efforts, decreased workload for medical staff, and improved effectiveness. The majority of the current AI tools used in health education are focused on complications monitoring, self-management, blood sugar and blood pressure monitoring, lifestyle advising, insulin injection guidance etc. Here, we make an effort to provide the most thorough illustration of the current AI techniques used to treat MS and its related complications from a variety of angles. In Table 2, we have included the top artificial intelligence programmes for managing and educating about MS.

Table 2: Details Related Research on MS and Related Conditions:

Method	Description	Application in MS related health conditions	References
Decision trees (DT)	A dataset is graphically represented as DT, which offers a highly natural approach to represent and comprehend rules by using tree-like structures to explain the data. Decision trees are made up of leaves, branches, and nodes. A leaf indicates a result, whereas a node reflects a choice. The DT always begins at the root node and expands downward by dividing the data into new nodes at each level. Classification issues are particularly well-solved by DT. The learning algorithm used to produce DT is frequently capable of extracting the information contained in a particular dataset. To make the information more readable for humans, the DT structure may be established after which sets of if-then rules can be used to express the knowledge. ID3 and C4.5 are two of the most often utilised algorithms. DT have been effectively used in the field of diabetes for a variety of activities, including type 2 diabetes screening and blood glucose categorization.	Diabetes management	Quinlan, 1981, Quinlan, 1993, Usher, *et al.*,2004, caballero-Ruiz, *et al.*, 2016
Support vector machines (SVM)	One of the most well-liked, adaptable, and potent ML (machine learning) algorithms used for classification at the moment is VM. Maximum-distance classification methods include SVM. By giving the greatest possible separation between the classifying plane and the nearest data points, they construct a hyperplane to divide two classes above and below it. "Support vectors" are the locations nearest to the boundary. SVM can only effectively tackle binary classification issues in their most basic form, but with a reasonably straightforward expansion, they can also handle multiclass classification problems.	To predict pre-diabetes and diabetes disease and in diabetes diagnosis.	Yu, *et al.*, 2010 and Kumari&Chitra, 2013
Computer Interpretable Guidelines (CIGs)	Clinical practise recommendations are valuable tools for raising the standard of treatment. Tools for supporting decision-making can be created through formalisation as CIGs utilising a sophisticated RBR framework. In another paper in this special section of the journal, clinical experience with gestational diabetes CIGs used for patients' and doctors' decision assistance is presented. Briefly stated, a pilot trial revealed improved compliance and patient satisfaction with blood glucose monitoring compared to typical care based on in-person visits.	Gestational Diabetes Management	Rigla, *et al.*, 2018

Artificial neural networks(ANN)	Deep learning ANN has recently demonstrated its ability to accurately and quickly detect diabetic retinopathy or diabetic macular edoema in retinal fundus pictures. The scientists have created an algorithm that determines the degree of diabetic retinopathy based on the brightness of the pixels in a fundus image. Large datasets of pictures were used to train the function, which was then assessed at a high specificity operating point and a high sensitivity operating point to get very high results.	Retinopathy Detection	Gulshan, *et al.*, 2016
Case-based reasoning (CBR)	Researchers from London's Imperial College have conducted one of the most pertinent experiences on the use of ES to patient decision assistance. They have created and tested a CBR-based bolus calculating algorithm. This technology, which is integrated into the patient's smartphone, makes use of data from continuous glucose monitoring. The advantages of this tool over standard bolus calculators have been demonstrated in a pilot feasibility study that has been published.	Insulin dose recommendat ion	Reddy, *et al.*, 2016
Fuzzy Logic (FL)	The use of FL to regulate BG has also been studied by several research teams. Mauseth et al. reported, for instance, on a FL controller intended to customise glycemic control. On the UVA/Padova T1D simulator, 30 computerised patients were used to test it. Next, they carried out a pilot research with 12 T1D patients to show that their strategy was workable. Later research suggested that high-fat meals and exercise might stress a fuzzy controller. Ten T1D patients participated in an experiment to evaluate this idea. The outcomes exposed flaws in their earlier strategy and eventually inspired changes to the FL controller. Simulated or virtual patients have been used to evaluate other FL methodologies. For instance, Miller et al. described using open-loop data to generate initial patient profiles using a fuzzy controller and learning algorithm. Another illustration was given by Dinani*et al.*who recommended combining fuzzy and sliding-mode controllers with the aim of using feedback to more aggressively regulate the insulin delivery rate.	Hypoglycemia detection	Mauseth, *et al.*, 2010, Mauseth, *et al.*, 2013, Yadav, *et al.*, 2016, Khooban, *et al.*, 2013, Fereydoune yan, *et al.*2013, Fereydoune ya, *et al.*, 2011, Miller, *et al.*, 2011, Dinani, *et al.*, 2015
Reinforcement learning (RL)	In order to optimise insulin infusion for individualised glucose management, an Actor-Critic method was suggested by Daskalaki et al. The system was tested on a virtual patient population. The findings showed that, particularly in individuals with low insulin sensitivity, their innovative tuning strategy reduced the incidence of severe hypoglycemia.	Glucose regulation	Daskalaki, *et al.*2016
Genetic algorithm (GA)	By generating a population of people (solutions) to optimisation problems, GA mimics natural selection. Recently, this method has been used to identify foot ulcers early. Segmentation, geometric transformation, and asymmetry analysis make up this method's three phases. GA imitates natural selection by creating a population of individuals (solutions to optimisation issues). This technique has recently been utilised to detect foot ulcers at an early stage. The three steps of this approach are segmentation, geometric transformation, and asymmetry analysis. (GA) that aims to avoid fluctuations brought on by derivatives in fuzzy design by optimising the values for two inputs and one output membership function. In the work of Catalogna*et al.*another GA was employed to assist an ANN controller. Instead of employing the trial-and-error method frequently used in ANN topology determination, the suggested GA in this scenario optimises network topology and learning characteristics. In keeping with earlier researchKhooban*et al* proposed a controller assisted by particle swarm optimization that optimizes the parameters of the glucose-insulin model	Bloodsugarm onitoringFoot ulcerpredictio n	Walsh, *et al.*, 2015, Gomez, *et al.*, Yap, *et al.*2018, Kaabouch, *et al.*2010, Catalogna, *et al.*, 2012

Actor-Critic algorithm	An Actor-Critical algorithm was used to optimise insulin infusion for individualised glucose management, and virtual patients were used to assess the system. The findings showed that, particularly in individuals with low insulin sensitivity, their innovative tuning strategy reduced the incidence of severe hypoglycemia.	Glucose regulation	Daskalaki, *et al.*, 2016
Continuous glucose Monitor(CGM)	Anticipating BG excursions may enable early detection of ineffective or subpar therapies. Therefore, data gathered from cutting-edge diabetes care technology, such CGM sensors, might result in real-time forecasts of future glucose levels. Because of the many physiological elements at play, such as the lag in measurements in the interstitial tissue and delays in meal and insulin absorption, predicting blood sugar levels is difficult. The challenge of forecasting BG readings is further made more difficult by CGM errors (around 9% of the mean absolute relative difference for the best sensors).	Diabetes management	Bailey, *et al.*2014
Continuous subcutaneous insulin infusion (CSII)	Similar to CGM, it employs basal insulin to cover meals or snacks (long-acting basal insulin injection and infusion at a constant basal rate, respectively) and bolus insulin (quick-acting bolus insulin injection and meal boluses, respectively).	Restoring blood glucose level	Contreras &Vehi, 2018
Multiple daily insulin injections (MDI)	For many insulin-dependent patients, calculating the proper insulin dosages and estimating carbohydrate intake are routine daily tasks. Bolus recommendations are made using information from prior insulin administrations, blood glucose readings, anticipated carbohydrate intake, and other patient-specific factors including insulin-to-carbohydrate ratio and insulin sensitivity. Because people must take into account a number of factors in order to maintain good glucose control, manually calculating bolus dosages and counting carbs can be complicated and difficult. Miscalculation of these numbers may also lead to chronic hyperglycemia episodes.	Restoring blood glucose level	Pesl, *et al.*, 2015, Herrero, *et al.*, 2014, Reddy, *et al.*, 2016, Pesl, *et al.*, 2017, Herrero, *et al.*2017
GoCARB system	automated carbohydrate counting-based dietary recommendations for diabetes patients. Pilot experiments demonstrate that their strategy, which is based on the use of computer vision techniques like feature extraction and SVM, is an outstanding aid. Additionally, we discovered a number of papers that supported their methodology by utilising the UVA/Padova patient simulator. In order to determine the best open- and closed-loop profiles for different meal compositions, Srinivasan et al. recommended using a set of insulin delivery profiles optimised using a PSO.	Dietary advice to diabetic patients	Srinivasan, *et al.*2014
METABO project	Since 2010, several research with the goal of creating DSSs to manage diabetes have been put forth. The METABO project is one of the most effective methods. This project includes sophisticated features such as monitoring, tools to stop future excursions, dynamic care route optimisation, knowledge discovery to identify patterns, and tools to direct weight reduction programmes. A number of pilot studies were carried out by the authors, including usability testing on 36 T1D patients. Another significant effort is MOSAIC, which aims to create a DSS for T2D management with an emphasis on data mining-based risk assessment of associated comorbidities. Another daily-life support system offers cutting-edge features including an integrated BG prediction tool based on evolutionary computing and a recommender system that uses case-based reasoning.	To manage diabetes therapies	Fioravanti, *et al.*, 2011, Fico, *et al.*, 2011, Fico, *et al.*, 2015, Fico, *et al.*, 2010, Guillen, *et al.*2011, Fico, *et al.*, 2014, Sacchi, *et al.*, 2015, Dagliati, *et al.*, 2016, Dagliati, *et al.*, 2018, Hidalgo, *et al.*, 2014

MediClass system	The MediClass system was used to give a weight control suggestion. The system, which was tested during the postpartum visits of 600 GDM patients, is based on the use of a natural language processing (NLP) algorithm. Tools for GDM patients were also studied by Rigla et al. They suggested a mobile app built on a telemedicine DSS with AI enhancements as a resource for GDM sufferers. Later, utilising a classifier built on a clustering algorithm and a decision tree learning method, they created a platform for remotely evaluating patients. 90 GDM patients participated in the system evaluation. The findings revealed a decrease in the amount of time physicians spent with patients and in face-to-face visits made for each patient.	Management of Gestational Diabetes	Hidalgo, *et al.*, 2014, Hazlehurst, *et al.*, 2014, Rigla, *et al.*, 2018, Caballero-Ruiz, *et al.*, 2017
Blood pressure A Convolutional Neural Network-Regression (CNN-R)	Ankishan*et al.* proposed the prediction of BP values from speech recordings of /a/ vowel, owing to its accurate reflection of acoustic characteristics in a short period of time. The authors recorded the /a/ vowel for 10 s from 86 participants with a mobile application that allows 16-bit resolution and 44 100 Hz sampling rate, giving 230 audio records. The referencing BP was measured with a cuff-based BP monitor. A Convolutional Neural Network-Regression (CNN-R) with two groups was trained to predict the BP values, and promising experimental results were shown. The accuracy was up to 93.7% and the RMSE is 0.236.	prediction of BP values	Ankishan, 2010
Signal-derived BP measurement, such as photoplethysmogram (PPG) or ECG signals	Pulse wave velocity refers to the velocity at which the pressure propagates through the circulatory system and is a major parameter for BP, of which pulse transit time and pulse arrival time are the indicators. These indicators can be derived from PPG and ECG signals so as to allow instantaneous estimation for BP. Monte-Moreno and colleagues has established a PPG-driven BP estimation ML model in year 2011 with preliminary success, where the model achieved a Grade B standard under protocol laid by the British Hypertension Society (BHS). Esmaelpoor and colleagues further devised a multistage deep neural network model to estimate SBP and diastolic blood pressure (DBP) separately from PPG signals in year 2020. The authors first made use of two CNN for morphological features extraction, followed by long short-term memory (LSTM) for temporal dependencies capture. The model not only met the standard laid by the Association for the Advancement of Medical Instrumentation (AAMI), but also was certified for Grade A standard under BHS, with mean (SD) of deviation for SBP and DBP estimations of +1.91(5.55) mmHg and +0.67(2.84) mmHg, respectively.	pulse transit time and pulse arrival time are the indicators	Monte-Moreno, 2011 &Esmaelpoor, *et al.*, 2020
Combination of residual network	The model was able to meet the AAMI(Advancement of Medical Instrumentation) standard for mean arterial pressure (MAP) and DBP (diastolic blood pressure)estimation. MAP and DBP estimation achieved Grade A under BHS standard. These findings have illustrated the viability of using either PPG or ECG signals for BP estimation; thus, wearable devices could render viable BP estimation based on quality AI algorithms adoption.	BP prediction	Miao, *et al.*, 2020

Obesity Personalized Food Recommender	A recommendation system may be thought of as a particular machine learning model that, given certain user data, predicts the "rating" or "preference". Modern recommendation systems currently frequently employ deep learning techniques based on embedding models. The retrieval of recipes is the main benefit of the food suggestion system. A innovative question-answering food recommendation system called PFoodReq is built on a substantial food knowledge base or graph. PFoodReq often responds to the user's query, such as "What goes well with bread for breakfast?" before outputting all of the model's recipes. The most suitable ingredients in these recipes are then scored, and the top-ranked dishes are suggested. A knowledge graph (KG) system called FlavorGraph uses relationships gleaned from culinary recipes and details on flavour compounds from food databases. Predicting complex food connections and choosing or optimising food pairings are the two major applications of FlavorGraph. Yum-me is a cutting-edge food image analysis model-integrated meal recommender that is nutrition-based. Two sources are used as its input variables: (I) a survey of the user's dietary needs and nutritional expectations; and (II) a visual interface that depicts the user's food choices. Based on a deep learning method, DeepFood can identify several items (food) in a picture by identifying potential areas or by classifying foods using a deep convolutional neural network (CNN). Market2Dish concentrated on the usability of user health profile and meal recommendations that were mindful of their health.	"rating" or "preference" of foods	Zhang, *et al.*, 2019, Chen, *et al.*, 2021, Park, *et al.*, 2021, Jiang, *et al.*, 2020, Xu, *et al.*, 2020
Nutrigenetic Model	The field of nutrigenetics focuses on understanding how diet and genetic information interact. A brand-new statistical technique called LC-N2G uses genetic algorithms to rank and find combinations of nutrients and gene expression. A nutrigenomics data platform called NutriGenomeDB, which uses the GSEA algorithm, gathers signature gene information from experimental nutrigenomics data gathered from the gene expression omnibus (GEO).	The interaction between nutrition and gene information.	Maharana& Nsoesie, 2018
Geographic Information System (GIS) Model	One of the hottest areas of contemporary public health research is the study of obesity-related issues using GIS data and methodologies. By seeing significant patterns in the built environment using satellite photos, a US team invented the use of deep learning algorithms to gauge the prevalence of obesity. The main concept is to uncover possible relationships between hidden characteristics and body mass index (BMI) by extracting hundreds of hidden elements from satellite photos. Sadly, the *framework is not accessible to the general public. MapMetadataEnrichment, a deep learning-based approach that can automatically generate tagged training map images from GIS data, is strongly suggested as an alternative framework. Spatial models could not be directly utilised to analyse GIS data to investigate obesity without a deep learning methodology. We offer the commonly used R-based programme GWmodel in this article for examining spatial heterogeneity using geographically weighted models. In a recent study, the relationship between socioeconomic factors, obesity, air temperature, and unhealthy behaviours in the USA was examined using a geographically weighted regression (GWR) model, which was based on the GWmodelpackage. This study serves as a classic example of the application of the GWmodel.*	obesity assessment	Hu, *et al.*, 2022, Kamel, *et al.*, 2019, Cao &Zheng, 2022, Lotfata, 2022, Lambert, *et al.*, 2021

Genetic Model	*Genetics is the study of genes and how certain traits or disorders are handed down through generations. The community is given access to an open platform for PGS research thanks to the polygenic score (PGS) database, which compiles published PGS information. Based on several genetic variations found across the genome, PRS calculates a person's hereditary risk for complicated illnesses. In fact, a polygenic risk score (PRS) might be thought of as a specific regression model; the PGS database has several obese PRS models, including PGP000017 and PGP000211. Impute.me is the first non-commercial platform for calculating and interpreting polygenic risk scores using data from direct-to-consumer genetic testing. Google introduced DeepVariant, a tool that employs deep neural networks to quickly and precisely detect variation sites from DNA sequencing data. The cardiovascular risk may be calculated using the NeuralCVD-based deep survival machine algorithm to avoid coronary heart disease. AI is used by DeepCOMBI in genome-wide association studies for analysis and discovery.*	obesity assessment	Folkersen, *et al.*, 2020, Yun, *et al.*2020, Steinfeldt, *et al.*, 2022, Mieth, *et al.*, 2021, Aoun, *et al.*, 2020
Microbiome Model	*The gut microbiota and general health are intimately connected. Numerous research point to particular alterations in the makeup and operation of the human gut microbiome as being related to obesity. Any investigation into the gut microbiota linked to obesity must first classify the various species to determine their relative abundance. DeepMicro, DeepMicrobes, SortMeRNA, q2-feature-classifier, swarm, and other common machine learning taxonomy classifiers are examples. We said that QIIME 2, the most widely used microbiome analysis tool, has q2 feature classifier incorporated. From the patient's microbiome sequencing data, ML models [GEDFN, MDeep, TaxoNN, and MetaPheno] also be used to predict the patient's phenotype or obesity. A repeatable preprocessing ML workflow for a microbiome is provided by MIPMLP.*	Gut microbiota and its relationship with obesity	Davis, 2016, Oh & Zhang, *et al.*, 2020, Liang, *et al.*, 2020, Kopoylova, *et al.*, 2012, Bokulich, et, al., 2018, Mahe, *et al.*, 2014, Bolyen, *et al.*, 2019, Zhu, *et al.*, 2019, Wang, *et al.*, 2021, Sharma, *et al.*, 2020, LaPierre, *et al.*, 2019, Jasner, *et al.*, 2021

Prediction of Diabetes and managing its complications:

In the present study, researchers from the United Kingdom employed a combination of quantitative and qualitative research methods to do a thorough review of 94 risk assessment models and scoring criteria pertaining to type 2 diabetes. The primary objective of this evaluation was to predict the likelihood of people having the aforementioned condition. Furthermore, a selection of these models and scoring approaches were implemented by them. The empirical results provided evidence for the robustness of several risk assessment methodologies and confirmed their efficacy across diverse cohorts of patients (Nobel, *et al.*, 2011). In their study, Mani *et al.* (2012) employed a combination of machine learning algorithms and electronic medical data from a cohort of 2,000 patients diagnosed with type 2 diabetes in order to forecast the likelihood of developing diabetes. The AUC values for the 6-month and 1-year projections were determined to be 0.8. This study showcased the feasibility of utilising electronic medical information to automatically forecast the occurrence of diabetes and identify individuals with a heightened susceptibility to its development. The use of an oral glucose tolerance test (OGTT) is deemed necessary for some individuals. Nevertheless, Fu *et al.* (2014) have developed a risk assessment model to effectively identify patients with a heightened susceptibility to postprandial hyperglycemia. In light of this matter, we contend that it is imperative to develop several assessment models tailored to different ethnic demographics. Additionally, the use of artificial intelligence (AI) models focusing on postprandial hyperglycemia has considerable potential in enhancing the precision of diabetes prediction.

Vascular pathologies and peripheral neuropathies are commonly observed as complications of diabetes and MS. The study conducted by researchers involved the analysis of retinal fundus images in adults, wherein it was shown that a deep learning system exhibited a sensitivity and specificity over 93% in the detection of diabetic retinopathies (Gulshan, *et.al*, 2016). In a retrospective analysis conducted by Takahashi *et al.*(2017) demonstrated that deep learning may be employed for the assessment of diabetic retinopathies. The study involved the examination of 9,939 posterior pole pictures obtained from a cohort of 2,740 individuals diagnosed with diabetes. Takahashi et al. introduced a novel artificial intelligence (AI) illness grading method in their study, which offers a means to assess the severity of diabetic retinopathies using a ranking mechanism. In a similar vein, the development of the "FootSnap" smartphone application aimed to provide a standardized approach for capturing images of diabetic feet (Yap, *et al.*2018). The study investigated the stability of FootSnap by conducting evaluations of different scenarios provided by many practitioners, comprising a cohort of 60 patients. The verification of the repeatability of the foot images was conducted by employing the Jaccard Similarity Index (JSI). The obtained JSI values for the diabetic foot condition ranged from 0.89 to 0.91, whereas the control group exhibited values ranging from 0.93 to 0.94. These findings suggest that the application demonstrated a high level of reliability. Kaabouche*et al.* (2010) employed a combination of asymmetry analysis and a genetic algorithm to conduct an analysis of thermal images. The objective of this study was to assist in the timely identification of foot ulcerations and the assessment of skin integrity. The present investigation revealed that the evaluated technology shown a high degree of accuracy in predicting potential foot ulcerations and proved to be a viable approach for identifying inflammation. Katigari*et al.* (2017) developed an expert system based on fuzzy logic principles, which was then employed for the analysis of medical information pertaining to 244 individuals diagnosed with diabetic neuropathies. The researchers made the finding that the system had a high level of accuracy in predicting the severity of diabetic neuropathies, achieving a 93% accuracy rate. Additionally, the system demonstrated an 89% specificity and an 89% sensitivity score.

The quantity of digital data collected from individuals diagnosed with MS is seeing a significant surge due to the progress made in information systems and technology. The aforementioned facts demonstrate that artificial intelligence technologies employing sophisticated and precise approaches can serve as useful management tools for assessing non-communicable disease datasets to provide valuable information. Given these circumstances, artificial intelligence (AI) plays a crucial role in these systems as a complementary component to traditional therapeutic methods.

Prediction of Blood Pressure Level with AI:

The barriers to reducing the burden of hypertension are inadequate BP control and ignorance of hypertension, however regular self-monitoring of BP could enable early detection of hypertension for better BP control (Uhlig, *et al.*, 2013) (Figure 3).

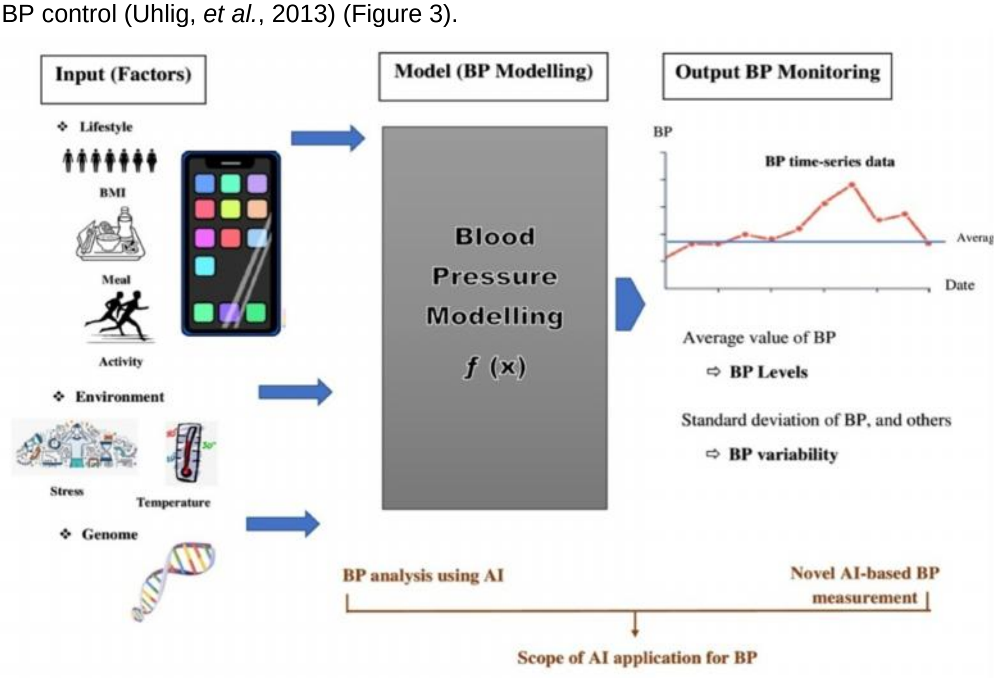

Figure 3. Scope of AI application in Blood Pressure Management

Despite the fact that cuff-based blood pressure measurement is universally regarded as the gold standard, new techniques for blood pressure monitoring from vital signals or even speech analysis have a great deal of promise to be included in wearable technology. Another emerging method is combining auscultatory waveforms and transdermal optical images with smartphone sound and image recording capabilities to estimate blood pressure. Due to the accurate and quick reflection of acoustic properties in voice recordings of the /a/ vowel, Ankishan *et al.*(2020) proposed the prediction of BP values. Using a mobile application that supports 16-bit resolution and a 44 100 Hz sampling rate, the authors collected 86 individuals' /a/ vowels for 10 seconds, yielding 230 audio records. Using a cuff-based blood pressure monitor, the reference BP was calculated. In order to forecast the BP values, a Convolutional Neural Network-Regression (CNN-R) with two groups was trained, and encouraging experimental results were reported. The RMSE is 0.236 and the accuracy reached 93.7%. Due to their compatibility with wearable technology like smartwatches, signal-derived BP assessment methods like photoplethysmogram (PPG) and ECG signals are also of great study interest. Pulse transit time and pulse arrival time are the indicators of pulse wave velocity, which is a key metric for blood pressure. Pulse wave velocity describes the speed at which pressure moves through the circulatory system. These indications can be created from PPG and ECG signals to enable real-time estimate of blood pressure. In 2011, Monte-Moreno and colleagues (2011) created a PPG-driven BP estimate ML model with some preliminary results; the model met the British Hypertension Society's (BHS) Grade B level. A multistage deep neural network model was also developed by Esmaelpoor and colleagues (2020) to estimate SBP and diastolic blood pressure (DBP) separately from PPG signals in 2020.The authors used long short-term memory (LSTM) to capture temporal relationships after first using two CNN for the extraction of morphological information. The model was certified for Grade A standard under BHS in addition to meeting the Association for the Advancement of Medical Instrumentation (AAMI) standard, with mean (SD) of deviation for SBP and DBP estimates of +1.91(5.55) mmHg and +0.67(2.84) mmHg, respectively. Miao, *et al.*, (2020) on the other hand, used a residual network and LSTM with a variety of ECG signals for continuous blood pressure monitoring. Once more, the model proved successful in estimating mean arterial pressure (MAP) and DBP to the AAMI standard. Under BHS standards, MAP and DBP estimation received a Grade A. These results demonstrate the feasibility of employing either PPG or ECG data for blood pressure calculation; hence, wearable technology could enable accurate BP estimate with the deployment of AI algorithms. New BP estimate techniques are being created more frequently to support smartphone compatibility. In addition to the proposed and tested smartphone auscultatory BP kits, Argha and colleagues (2019) have improved the methodology for more precise BP estimate using LSTM and recurrent neural network (RNN). Auscultatory sound is used to extract Cuff pressure and Korotkoff sounds for neural network construction. SBP estimation results with a mean (SD) of 1.5 (4.8) mmHg are graded as Grade A according to BHS standards. Transdermal optical imaging technology is another significant advancement in blood pressure measurement, as promoted by Luo and colleagues (Luo, *et al.*, 2019) in 2019. The authors suggested that the ML model for estimating BP may employ the tiny changes in facial blood flow recorded by a video taken with a smartphone camera as inputs. The average measurement bias (SD) for SBP and DBP is +0.4 (7.3) mmHg and 0.2 (6.0) mmHg, respectively, after training, testing, and validation using data gathered from 1328 normotensive people. Due to their great adaptability with wearable devices, advances in cuff-less blood pressure measures may prove to be substitutes for cuff-based devices in the effort to encourage self-monitoring behaviors. However, due to the fact that not a single cuff-free wearable device on the market has been validated in accordance with the International Validation Standard, caution must still be used with regard to the clinical validity of measured data (Picone, *et al.*, 2020) Since hypertension is one of the most common hidden chronic disorders, it is extremely difficult to keep patients motivated and compliant. AI might eliminate tiresome tasks and free up more time for doctors to train and concentrate on patient motivation, empathy, and compassion. Such advancements could enhance patient-centered care and systematic team approaches to adherence intervention (Kerasidou, 2020 &Krittanawong, 2018).

Lifestyle Modification and AI applications:

Understanding the impact of carbohydrates on blood glucose levels and the varying carbohydrate content in different dietary regimens is a fundamental aspect of managing MS or diabetes. It is important to compute the overall carbohydrate consumption of the patient in order to effectively customize the dosage of insulin. In the 1990s, researchers utilized a computerized equipment known as a "food metre" to record the dietary intake of 21 individuals with diabetes. This technology enabled the researchers to document the specific types and quantities of food and drinks ingested by the participants over the course of one week (Rivellese, *et al.*, 1991) This approach unveiled a means of examining the dietary preferences and personal characteristics of patients to provide recommendations for tailoring insulin dosage on an individual level, resulting in improved management of blood glucose levels. Based on the findings of an experimental study, it has been seen that including fat and protein into the calculation of insulin dosages might lead to a significant reduction in levels of hemoglobin A1C (HbA1c), in comparison to relying only on carbohydrate levels (Pamkowska, *et al.*, 2012). Currently, there is ongoing development of software programs that employ visual analysis methods to examine nutritional content swiftly and precisely. The proposed approach allows patients to efficiently get relevant nutritional information, such as calorie and carbohydrate content, through the use of smartphone photographs. This information can assist them in making informed decisions regarding their dietary choices (Froisland & Arsand, 2015). Oka *et al.*(2019) employed deep learning and remote communications technologies to automatically assess the nutritional intake of patients by evaluating photographs of their meals. Based on the results of a 12-month randomized controlled trial, it was observed that the HbA1c level exhibited a standard deviation and average variation of 0.3%. The findings of this study indicate that the outcomes of utilizing automated AI help for dietary intervention are similar to those achieved with in-person support from a human dietician. Consequently, the implementation of these strategies can effectively reduce the burden on human specialists and enhance the effectiveness of dietary guidance for individuals with diabetes. Zeevi*et al.* (2015) developed a machine learning system capable of integrating blood parameters, food preferences, blood measures, and physical activity data obtained from a cohort consisting of 800 individuals. Subsequently, it was verified that the algorithm demonstrated accurate prognostication of postprandial glycemic reactions to actual meals consumed by individuals within a cohort consisting of 100 participants. The results of this study indicate that personalized diets can effectively reduce the increase in postprandial glucose levels and mitigate its metabolic consequences.

Exercise or physical activity:

Effective exercise helps regulate blood sugar levels as well as lipid profiles and lowers the risk of cardiovascular problems. Using machine learning to reanalyze data, the Action for Health in Diabetes (Look AHEAD) trial shown that type 2 diabetes patients can gain from intensive lifestyle interventions that include weight loss, which can also lower the incidence of cardiovascular events (Baun, *et al.*, 2017). Weight loss and dedication to a balanced diet can be used as preventive strategies when diabetes is still in its early stages. A decision support system utilizing machine learning was proposed by Everett *et al.*, (2018) who discovered that it could encourage users to adhere to their goals for weight loss and physical activity, hence lowering their chance of getting diabetes. A regression model was suggested by Jacobs *et al.* (2018) to automatically analyse the exercise levels of patients wearing accelerometers and cardiac monitors as well as to track changes in blood glucose levels that took place while the participants were exercising. 13 individuals with type 1 diabetes were evaluated, and the findings showed a sensitivity of 97.2% and a specificity of 99.5%.

We believe that AI would play a vital role in providing personalized lifestyle counseling and assisting in the control of MS as a result of the technological advancements in picture visualization and the widespread usage of wearable technology.

AI-based evaluation of food and nutrient consumption:

There are three distinct approaches utilized in assessing an individual's three-day food consumption: a three-day food weighment survey, a twenty-four-hour recall of food intake, and a food diary. The implementation of these procedures necessitates a considerable amount of time, as well as the involvement of professionals possessing specialized training to conduct patient interviews and gather relevant data. The primary source of information utilized by investigators is predominantly derived from the recollections of the individual under examination. The user did not provide any text to rewrite. Consequently, the precision of the data is relatively diminished, especially when considering individuals who are advanced in age or afflicted with cognitive impairments such as dementia and Alzheimer's disease, which can adversely affect memory function. In such circumstances, it might pose challenges to provide sufficient nutrition and accurately assess the intake of actual food and nutrients. Adequate nutrition plays a crucial role in safeguarding well-being and mitigating the functional deterioration associated with aging (Sharma, *et al.*, 2020, WHO, 2021, Ghosh, *et al.*, 2022, Singh, *et al.*, 2023, Choudhury, *et al.*, 2022, Ghosh, *et al.*, 2022, Ghosh, *et al.*, 2021, Ghosh, *et al.*, 2020, Ghosh, *et al.*, 2021, Ghosh, *et al.*, 2023, Ghosh, 2023, Choudhary, *et al.*2024) and other sickness conditions. The process of strategizing and assessing the effectiveness of therapeutic meals for patients receiving medical treatment relies on the acquisition of precise and dependable data on their food consumption and nutrient intake. Previous research has indicated that the reliability of data obtained by conventional methods may be compromised due to the potential for inaccuracies in estimating food consumption. Furthermore, the available data does not provide any evidence on the veracity of the menu that was consumed. In order to tackle the issue at hand, Eskin & Mihailidis (2012) utilised a facial recognition or vision-based system for the purpose of identifying the food products and quantities that were consumed. In previous times, the advancement of food recognition and portion estimation predominantly relied on the utilization of facial recognition techniques inside user interfaces designed for mobile devices. Segmentation is a crucial procedure in facilitating image analysis, since it involves the division of the original input into smaller, more manageable components. The segmentation process consists of three fundamental processes, namely classification, object identification, and segmentation. During the classification step, the programme partitions the picture into many classes. Food items arranged on a plate can be classified into many categories, such as apples, eggs, bread (either white or brown), butter, and so on. In the context of object detection, the computer employs a rectangular shape to enclose various items such as apples, eggs, bread, and butter positioned both on the plate and in its immediate vicinity. This enables the computer to effectively identify and discern these categorized things. Subsequently, the computer conducted an assessment of the identified components or segments of the item and ascertained their association with a specific object. The datasets utilized in these systems will comprise photographs that are employed for the purpose of face recognition. The standardizing of fast food goods was facilitated by the utilization of comparable compilations of photos. The provided text consists of two numerical values, specifically (Zhu, *et al.*, 2010 , Chen, *et al.*, 2009). The utilization of datasets including images of food components was employed for the purpose of standardizing recipes. By employing suitable automated analytic tools and employing mathematical and statistical approaches, it is possible to determine the most effective choice for ingredient or process technology. The use of webcams situated above the plate is an essential requirement in the development of an artificial intelligence (AI)-driven nutritional evaluation system designed specifically for the elderly and individuals with illnesses. The acquired picture will undergo three distinct steps of analysis: segmentation, recognition, and calculation of component size. The use of AI-based food and nutrient intake monitoring data poses challenges due to the lack of a universally applicable programme that accommodates diverse cuisines and eating patterns around the globe. Acquiring the necessary datasets for deep learning poses challenges due to the regional diversity in the culinary preferences of the population. Furthermore, there is considerable variation in the dietary provisions offered to patients among hospitals, even within a small geographical area. As previously said, MS management and education are crucial components of enhancing the effectiveness of disease management. As a result, it has become unavoidable for management and education strategies to be combined with AI and mobile health technologies. We have observed that the diverse spectrum of AI-based approaches has both advantages and disadvantages. One algorithm's usefulness, though, depends on the problem and the available data. For instance, depending on the classification criteria and typical data distribution, a classification analysis for MS may in certain cases produce positive results when standard methods provided by widely used data analysis tools are applied directly. To infer a moreprecise arrangement of the analyzing object, more sophisticated models must occasionally be built.

Conclusion

In summary, although the utilization of artificial intelligence in educational interventions holds potential, it is important to acknowledge its inherent limits. Although there is a growing body of literature on the utilization of digital and intelligent tools in the management of MS, a significant portion of the existing studies suffer from limitations such as inadequate sample sizes or a failure to establish the clinical significance of the intervention outcomes. In order to achieve comprehensive and effective implementation of AI-based models and the development of personalized educational intervention plans for patients with diverse requirements, the following objectives must be fulfilled: The proposed approach involves several key steps: (1) aggregating extensive amounts of patient data to generate personalized patient profiles; (2) establishing a comprehensive integration of medical expertise and artificial intelligence (AI) technologies; (3) conducting standardized, randomized controlled trials that encompass clinical practice; (4) fostering active collaboration between physicians and patients within a system aimed at optimizing effectiveness; and (5) consistently updating and The resolution of these issues necessitates scientific inquiry, legislative measures, and the establishment of standardized practices within the relevant industries. Additional challenges in the present day encompass concerns pertaining to the safeguarding of user data and privacy, with technological, philosophical, ethical, and legal complexities. The issue of information security is a novel one that has arisen in the era of artificial intelligence. Further efforts will be necessary to promote the expeditious and effective assimilation of artificial intelligence (AI) within the medical domains.

Notwithstanding these challenges, the advancements in utilizing artificial intelligence (AI) in the field of medicine have been rapidly evolving, and it would be imprudent to disregard the potential and scholarly value of these applications. Future health education on MS has the potential to provide comprehensive, personalized, and sophisticated training by leveraging integrated and comprehensive uses of specific artificial intelligence (AI) technology. This intervention will provide patients with long-term protection and guidance throughout their lifespan.

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Conflict of Interest:

There are no conflicts of interest.

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