AI-Driven Analysis of Lifestyle Patterns for Early Detection of Metabolic Disorders

Tulasi Naga Subhash Polineni[1], Venkata Krishna Azith Teja Ganti[2], Kiran Kumar Maguluri[3], Dr. P.R. Sudha Rani[4]

[1]Sr Data Engineer, Exelon, Baltimore MD, ORCID: 0009-0004-0068-6310
[2]Sr Data Support Engineer, Microsoft Corporation, Charlotte NC, ORCID: 0009-0001-3911-1627
[3]IT systems Architect, Cigna Plano Texas, ORCID: 0009-0006-9371-058X
[4]Professor, Department of CSE, SVECW, Bhimavaram, AP, India,

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ABSTRACT

Convergence of medical and consumer electronics, as well as data analysis techniques such as artificial intelligence, allows early detection and prevention of diseases such as diabetes. Using custom-designed wearable electronics to monitor heart rate, SpO2, location, and skin impedance continuously over more than a year allows the detection of changes in lifestyle patterns coinciding with serious modifications in physiology related to the pre-diabetic state several months before fasting glycemia exceeds the 125 mg/dL diagnostic threshold. The recorded data reveal differences in lifestyle patterns between individuals who exhibited major versus small normal-to-pre-diabetic transitions, allowing a preliminary AI-driven statistical analysis of pre-diabetic indicators. Additionally, urban mobility, the intake of both food and drink, and sleep efficiency were identified and quantified as the most indicative types of behavior in this context.

Keywords: Convergence, Medical Electronics, Consumer Electronics, Data Analysis, Artificial Intelligence, Early Detection, Disease Prevention, Diabetes, Wearable Electronics, Heart Rate Monitoring, SpO2, Location Tracking, Skin Impedance, Lifestyle Patterns, Pre-Diabetic State, Fasting Glycemia, AI-Driven Analysis, Statistical Analysis, Urban Mobility, Behavior Quantification.

1. INTRODUCTION

Researchers spend an enormous amount of resources investigating how dietary habits and unhealthy lifestyle factors are significantly associated with increased prevalence of various metabolic chronic disorders, such as diabetes mellitus, hypertension, and metabolic syndrome. This background motivates us to explore how a self-controlled lifestyle could help decrease the prevalence of these disorders. The logical way to achieve the objective is to develop an AI-driven technique that could analyze various lifestyle habits, identify relevant lifestyle patterns, and then use these patterns to efficiently screen and predict individuals at risk of metabolic diseases well before detection. Needless to say, providing advice or support on the basis of detected patterns could significantly help reduce the risk of these diseases. Towards this goal, we propose AI-based pattern recognition techniques that could predict individuals at risk of specified metabolic disorders and further signify those significant habits related to these diseases in a particular individual.

Fig 1: AI for Disease Prediction

1.1. Background and Significance

Artificial intelligence (AI) is becoming more integrated into human daily life. Since the development and implementation of smartphones and intelligent home appliances, the activity and lifestyle patterns of humans are tracked, stored, and saved in the cloud. In addition, numerous wearable devices have been developed to continuously monitor human health and wellness. Many studies have been published to investigate whether the collected activity and lifestyle patterns can be analyzed and correlated to specific epidemiological diseases, at both individual and population levels. These collected AI data, if used properly, can provide biomedical researchers and clinical doctors with a personal, precise, and predictive approach to investigate, intervene, and manage noncommunicable diseases (NCDs), especially metabolic disorders. Currently, NCDs account for more than 60% of the global health burden. Unlike traditional communicable diseases caused by bacteria and viruses, NCDs, led by metabolic disorders such as type 2 diabetes, overweight, and obesity, have complex etiology and are related to nearly all conditions of modern human lifestyle, including dietary patterns, physical activity, smoking, and drinking. Early detection and prevention of metabolic disorders have become one of the most compelling needs and problems for both public and personal healthcare. Utilizing AI technology to analyze and recognize lifestyle patterns for the early detection of individuals who are at risk of developing metabolic disorders is noninvasive, cost-effective, and feasible.

1.2. Research Objectives

The main purpose of the present study is 1) to identify typical lifestyle patterns using AI-driven methods from lifestyle-related big data, including dietary, metabolic, and physical activity data; 2) to develop predictive algorithms for early warning based on the identified lifestyle patterns; and 3) to determine the practical intervention points. For the AI-driven tasks, the data will be preprocessed under different functional aspects. The data will be integrated to maximize the comprehensive use of data sources. The lifestyle pattern identification tasks will be performed using the shape of data, rather than streamlined data. The advanced machine learning tasks will be performed separately for multiple-participant data for improvement by revealing the participants' clusters. The novel metabolic status predictor model will be developed utilizing the ranked, time-series component of keyword features.

We expect the evidence-based determinations of the practical intervention points, previously unknown factors, or behavioral associations, with increased performance compared with conventional methods by utilizing AI technology. Our research work represents a small step to push the consequences of LSBD-related AI forward. This newfound knowledge will positively impact the fields of public health, eHealth, and personal medicine. That is, personalized lifestyle coaching according to the individual's lifestyle pattern can alleviate type 2 diabetes mellitus. Clinically identifying and warning individuals who are exposed to high-risk metabolic syndrome and NAFLD by regular health check-ups can prevent further damage. It provides a preventive service via a digital application that is affordable, accessible, and easy to use. The research is expected to contribute to improving public health.

$$L_p = \sum_{i=1}^{n} w_i x_i + b$$

Equation 1: Lifestyle Pattern Detection Model

L_p: Lifestyle pattern score for metabolic disorder detection.
x_i: Variables such as heart rate, SpO2, sleep patterns, and location.
w_i: Weights for each feature x_i.
b: Bias term.

2. METABOLIC DISORDERS: TYPES AND RISK FACTORS

The human body relies on energy supply from food to sustain life. The energy derived from food is used to perform daily functions. However, if the body's energy production and demand do not meet, a person's metabolic state may become unbalanced, leading to a metabolic disorder. Over time, this can lead to diseases. Metabolic disorder-related diseases can be separated into three different types due to the variety of metabolic routes: type I diabetes, type II diabetes, and metabolic syndrome. Most of these disorders can be misdiagnosed until severe health problems occur, such as liver and kidney problems, vascular dysfunction, and heart disease. Therefore, early detection of abnormalities in metabolism is essential for health care, especially for those with high-risk personalities. Treatment for metabolic disorders can be achieved through a multidisciplinary approach by changing the lifestyle. Such beneficial factors include food symmetry evaluation, a personalized diet plan, preventing weight gain, increasing physical activity, and monitoring circadian clock variations. Therefore, by tracking the lifestyle of the concerned person carefully, our study applied the advantages of AI to fuse such factors together and built a potential early detection system for metabolic disorders. More detailed types of metabolic disorders and risk factors will be introduced in the following sections.

2.1. Overview of Metabolic Disorders

The human body is made up of many organs and systems that work together tirelessly in an incredible and very complex machine. The inner workings of the body, also known as metabolism, are very important for keeping this machine in good working order. This metabolism is controlled by a number of hormones, and the kidneys, liver, and intestines play major roles in this process. When this intricate process of metabolism doesn't work the way it is supposed to, a number of very complex diseases called metabolism-related diseases emerge. Obesity is one of the most important sources of this problem, and it is at the root of diseases like type 2 diabetes that are all increasing at a very rapid rate, transcending national borders. These diseases also result in increased healthcare costs, increased time lost from work, decreased productivity, a decreased quality of life, and even death because of complications.

Metabolism-related diseases not only have various underlying problems, but they also have several health issues such as cardiovascular diseases, renal failure, stroke, retinopathy, musculoskeletal deformities, gum pain, or even the development of several forms of mobile cancer. Metabolic diseases are caused by complex interactions, including genes, behavior, and the environment. While changing the balance of these interactive components in a way that adversely affects metabolism and leads to many chronic diseases, changes in people's lifestyle patterns have particularly increased obesity. Economic welfare and changes in people's work habits have resulted in increased energy intake and decreased energy output, which led to being overweight and obese, thereby increasing the prevalence of these chronic diseases.

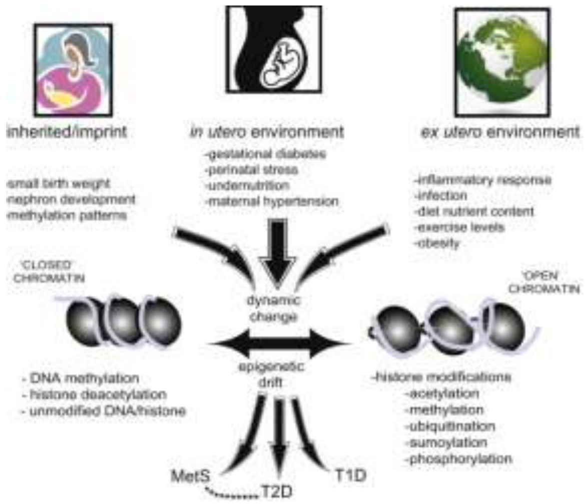

Fig 2: Metabolic Disorder - an overview

2.2. Common Risk Factors

The signs that a person may have one of the common metabolic disorders are often attributed to obesity, type 2 diabetes mellitus, arterial hypertension, and joint diseases. Indeed, the main early signs of all of these disorders are related to changes in lifestyle patterns and are correlated to unhealthy habits. They include overconsumption of energy-dense foods that are high in fat, added sugar, and added salt, physical inactivity, smoking, alcohol abuse, fast weight gain, and inability to maintain that weight, as well as the development of psycho emotional disturbances due to the impact of all these factors. These risk factors contrast sharply with those for type 1 and gestational diabetes, which relate mainly to genetics, inflammation, and hormonal changes. At the same time, these modifiable risk factors also appear to be interconnected and to be influenced by the same nutrients and physiologically active substances. Yet, the implementation of a complex intervention for changing all of these factors does not offer the same benefits or have the same cost-effective performance in the prevention of type 2 diabetes.

3. ROLE OF LIFESTYLE PATTERNS IN METABOLIC DISORDERS

Metabolic disorders and chronic non-communicable diseases such as type 2 diabetes, cardiovascular disease, and hepatosteatosis share some lifestyle and metabolic risk factors that can be related to daily life habits. They are caused or exacerbated by an excess of energy intake due to dietary imbalance and physical inactivity, wherein pharmacotherapy resolves the symptomatic problems with limited effectiveness. A healthy lifestyle intervention positively affects several metabolic parameters and reduces the risk of metabolic disorders. On the other hand, evidence shows that adherence to a healthy lifestyle is declining among young people and adolescents, resulting in worsening metabolic parameters and a higher probability of presenting a pre-pathological situation sometimes followed by the establishment of a metabolic disease. These data strongly advocate the necessity to promote a regular healthy lifestyle from childhood, with the opportunity to develop a program for evaluating and monitoring the changes in biological parameters during lifestyle changes, useful for better understanding the risk conditions of children and adolescents.

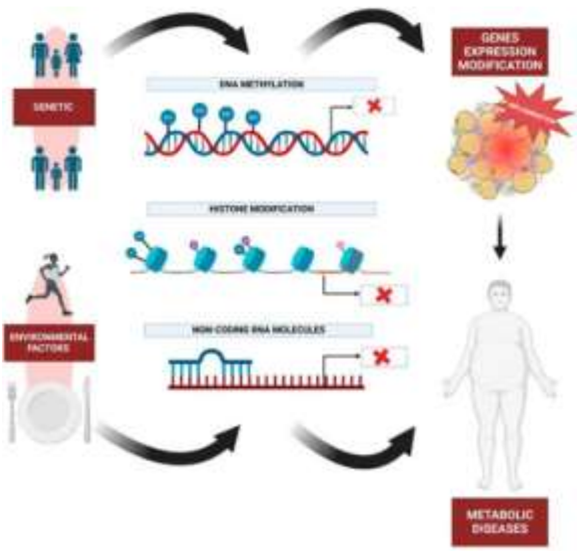

Fig 3: Insights and Potential Therapeutic Interventions in Metabolic Diseases

3.1. Dietary Habits

Analytical Approach. Information on persons' dietary habits is often acquired noninvasively, namely from day-to-day self-report food journals that reflect real-world conditions. The binary responses of the representations of both habitual food/product usage and consumption estimated from the data are used as the model outputs. To train learning models, the input dimensions are harmonized by grouping dietary habit indicators into food types that are defined using expert knowledge. Additionally, various basic aggregated dietary indices are calculated from the self-report journal data in an expectable way. Note that, from time to time, the applications of the dietary data-driven models have shown themselves to improve compared with traditional self-report dietitian practices.

Resulting dietary habit features visually display the importance of carbohydrate and alcohol consumption with respect to the ideal weight change synthesized from the analysis of all trait values available in the present investigation regarding each assigned anthropometric measurement up to the body mass index. During diet advancement, dietary information can better reflect the advanced stage of carbohydrate and water metabolism since it is the condition under the strongest ground of the metabolic health core, which includes some degree of shareable vitamin balance. Various metrics can more consistently estimate alcohol metabolism, gastrointestinal process performance quality, sugar compound metabolism, etc. In the context of these sets of expert knowledge, the overall study results point to a better health condition for healthcare applications, which is unreachable by doing the same tasks using only anthropometric measurements.

3.2. Physical Activity Levels

Individuals can be divided into different physical activity levels (PA levels) according to their daily activities. It is widely accepted that high PA levels can promote health. To monitor the physical activities of users over a long period of time, we focused on our daily lifestyle, mainly daily step count, which can be easily measured by fitness trackers, smartphones, or sensor systems in our routine activities. The daily step count can represent the users' biosignals. By performing a time series of steps for users across the year, we can detect the change in their lifestyles and variations in response to external factors. The distribution is illustrated. Males have higher step counts than females, and teenagers walk more than any other age group. The PA level fluctuated significantly at different stages of the pandemic. Many studies have discussed the distribution of daily step counts under a specific variable, such as different age levels, different BMI, etc. These step count distributions were usually utilized for specific groups to investigate their obesity patterns, to invite them to participate in health promotion programs, to evaluate the effectiveness of intervention programs, and to develop predictive models for different diseases.

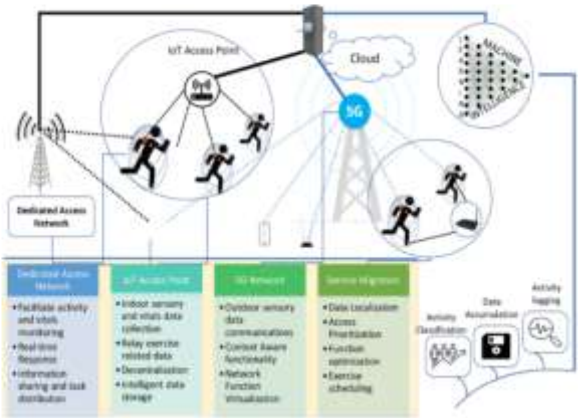

Fig 4: Physical Activity Monitoring and Classification

3.3. Sleep Patterns

Sleep duration, quality, and schedule have powerful effects on many aspects of physiological and mental well-being. Sleep deficiency has been associated with a variety of metabolic, endocrine, and immune disorders. Stressing through vigorous activities or orthorexic dieting are common measures that are taken in the dieting process during the weight loss period and have been associated with sleep disturbance and insomnia. The entire work is dependent on the disclosed effect of such sleep disturbance on lifestyle entities. In our dataset, sleep patterns specifically related to weekdays and free days are present in most of the subjects. Accordingly, we included the following AGDs based on these two sets of data: sleep_start, sleep_end, awake_duration, sleep_duration, and bedtime_change_on_weekdays_free_days. In our study, we used the patients' sleep patterns on free days and weekdays as key behavior indicators and determined that these indicators showed a discriminatory characteristic between groups with and without metabolic disorders.

In particular, our experimental results clearly demonstrate that patients in the metabolic disorder group had an abnormality in the sleep pattern, with the following typical characteristics of late-started sleep, short sleep period, and large changes in the sleep initiation time on weekdays versus free days during the week, which causes problems with staying awake during normal work hours and results in a greater reduction of weekend total sleep time and late-week bedtime recurrences, respectively. The importance of early detection of these restricted sleep schedules and validated relationships with health outcomes, such as obesity, diabetes, and overt metabolic syndrome, reinforces the relevance of long-term affected quality of life and the occurrence of diseases. Overall, sleep patterns are the most identifiable indicators of abnormalities in the circadian rhythms. When the sleep schedule shifts, e.g., when people sleep only 5 or 6 hours per night, sleep is sensitive to social restrictions based on work schedules. These abnormal patterns of sleep are usually associated with an insufficient sleep schedule, leading to insufficient sleep and fatigue. In our dataset, sleep patterns specifically related to weekdays and free days are present in most of the subjects.

$$R_d = \sigma\left(\sum_{i=1}^{n} \beta_i x_i + \theta\right)$$

Equation 2: AI-Driven Risk Prediction Model

R_d: Risk score for metabolic disorder (e.g., pre-diabetes).

β_i: Coefficients for each lifestyle factor x_i.

x_i: Input variables (e.g., mobility, diet, sleep).

θ: Bias term.

σ: Activation function (e.g., sigmoid).

4. ARTIFICIAL INTELLIGENCE IN HEALTH AND MEDICINE

In the past few years, healthcare has become a field of interest for big data, artificial intelligence, and data science. AI algorithms have been trained with deep learning to outperform human performance in several medical and clinical tasks, including disease detection, radiology image tissue classification, diagnosis, and therapeutic planning. AI has been demonstrated to have potential applications in cancer diagnosis, predictions of drug administration, and other early prognosis tasks, including mental conditions. There are also several commercial AI applications already available for healthcare providers to reduce healthcare costs and improve patient outcomes.

However, while the adoption of AI by the healthcare industry is progressing, there are still many open challenges and ethical considerations to address in order to demonstrate the safety, security, and effectiveness of healthcare AI applications. In this chapter, we present an open-source project to design and deliver AI-driven health research and clinical solutions using data made available by individuals and captured through lifestyle data points. This project is an ecosystem of tools, libraries, data, and models to gather, analyze, and uncover potential and early evidence of metabolic disorders using data from several domains of human lifestyle by employing data anonymization and differential privacy techniques.

Fig 5: Artificial intelligence in clinical medicine

4.1. Applications in Disease Detection

Your diet signature can reveal your health. For disease detection, we propose to incorporate dietary information—an active conversation happens between our diet and our intestines, while diet can also serve as a prebiotic to guide inter-bacterial cross-feeding and modulate health outcomes. This dietary signature assumes that each individual consumes a unique menu, and we could capture their lifestyle influence, which serves as a key indicator for early prediction of metabolic disorders. Recently, the high-resolution metabolites and genes diet signatures have been reported. The potential dietary signatures could complement traditional genomics, microbiomics, and metabolomics data to facilitate the prediction of whether an individual has certain metabolic diseases. Specifically, this solution would provide an early predictor of metabolic disorders for people to adjust their lifestyles and thus drive real-time, personalized precision health. Summary: A computer coach employing AI techniques has one of many applications: to tell if you might have a keep-fit issue in the future. If so, the coach can offer advice based on your unique diet, microbiome, and atmosphere tracking. In the healthcare frontier, we would create a computational approach to identify what aspects cause fluctuations in physical measurements of our body and diseases. In the algorithmic discovery phase, data from three primary sources would be leveraged—the microbiome population data, over 60,000 food intake records, and the continuous tracking of body weight and cognitive function. The computer coach harnesses your daily meals, tracks your lifestyle patterns, and identifies your health predictors. Our effort might serve as one piece of the puzzle for alternatives to regulate your lifestyle and create health-supported food products in addition to prevention or diagnosis by medicine.

4.2. Advantages and Limitations

Advanced AI methods have advantages and limitations that a lifestyle-focused diabetes screening and risk reduction tool for young people must take into account. On the plus side, our open models for computer vision, NLP, and recommendation can be separately trained on alternative data that replaces health-related image categories, employs new languages, or is useful for other domains. This could make it easier to ensure the tool can be truly universal and would also allow for updates in different domains without any significant additional costs. Including new data or adding a new language is relatively easy and can be implemented quickly, and even a continuous change in the production environment is conceivable. Developing the models took a few months and requires access to large quantities of data and capable personnel. Further refinements are, however, feasible relatively quickly and easily. Reflection, time, and publication requirements for adaptations would add more time.

Requirements for model-specific data: It would be a good idea to train the global models to be locally appropriate by, for instance, only accepting relevant local alternative data or by fine-tuning a global model using additional local alternative data. The images for information retrieval should not be obtained from private photo archives. We therefore recommend linking to search engines and official photo collections that are kept up-to-date and readily available. Since we process images and information from young people with the help of supervised models, the focus must always be on privacy, fairness, and social benefit, and we must ask, notwithstanding a good primary input signal and a good predictive success rate, if that particular developmental step should be done. Before thinking about the best way to do things, we suggest first seriously considering whether one should fundamentally reconsider doing it.

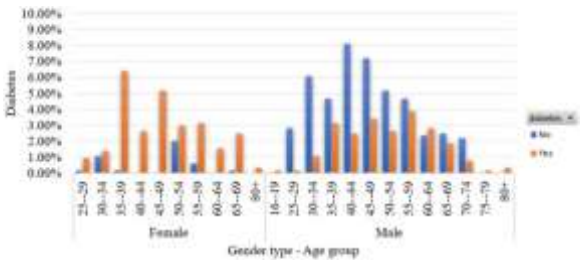

Fig 6: Data-Driven Machine-Learning Methods for Diabetes Risk Prediction

5. AI-DRIVEN ANALYSIS OF LIFESTYLE PATTERNS

With all the digital footprints collected by our app, we have been able to understand very well the diversified lifestyle of individuals. To begin with, we have population-wise average wake-sleep patterns over a two-week period according to seasons. We have grouped all 52 weeks into four seasonal sets: spring, summer, autumn, and winter, and provided the corresponding lifestyle patterns in these datasets. In China, spring, summer, autumn, and winter start in March, June, September, and December and end in May, August, November, and February, respectively. We observe that overall, the wake-sleep pattern is delayed longer on Fridays and

Saturdays. The analysis on the percentage of sleep and wake time versus wake time on a self-reporting basis yields that most of our subjects have a very regular wake-sleep pattern. However, we can still see that there is a small portion of people who exhibit poor sleep regularity. To investigate sleep consistency, besides analyzing inter-day variations, we also performed a trend study for each individual over a two-week duration.
Main meals are breakfast, lunch, and dinner, and currently in our system, we can tell the population-wise and on an individual basis when these main meals happen. On average, it is observed that urban residents have later breakfasts than rural people, but an earlier dinner time. Moreover, approximately 60 percent of the people share similar meal patterns on weekdays and weekends, while the other 40 percent tend to wake up late and skip breakfast as well. After artificial intelligence-based food image recognition and a calorie-counting mechanism, we are going to work further to investigate how the three main meals affect the probability of having type 2 diabetes mellitus. The dining out frequency and the duration of dining are two lifestyle indices we investigated, and people usually dine out two times per day, among which dining out for dinner is the most favored, with approximately 30 percent of subjects choosing to do so.

5.1. Data Collection and Processing

In this work, we focus on health condition monitoring and dependency pattern detection for metabolic disorders like obesity, type 2 diabetes, and non-alcoholic fatty liver. To analyze lifestyle patterns of the population, we used diary records of multi-institutional studies. Our first data source contains 91,755 records collected from 65 people over two years. To permit dose responses and addiction analysis, durations in this dataset were rounded according to the following rule: 5–15 minutes are treated as 0.25 hours, 15–30 minutes are rounded to 0.5 hours, 30–60 minutes are treated as 1 hour, and so on. Another source is even larger, containing 77,334 records for 141 people. They were studying their behavior for 8,000 virtual dollars, participating in the experiment with point-based rewards where people buy one extra life per day and earn points from walking and working. Both datasets include leisure, eating, and working activities with start and end times and have volunteer food diaries as additional data sources to verify activities in labeled periods.
The initial pre-processing step was to merge and filter both datasets. We transformed 60 activity types into 10 categories: leisure activities (passive), food assortment (eat), active leisure/walk, babble (talk), physical activities, desk work, software work, meeting, offshore work, and work for improving health. Then we converted food labels to five diet types: no conflict, unhealthy while eating, reasonable while eating, complying, and unclear. Each activity record was marked with three types of numeric attributes: food marks, time labels, and activity degrees. All time-distributed activities were converted to one consistent unit with two types of minutes: weekday minutes and weekend minutes according to the 'Passive–Active–Rest Neutral–Active–Passive' model. The last collected data was the BMI index, which was calculated periodically from scales installed in the participating rooms. Then the data from the two-year study was divided into two parts with observations of normal BMI and observations of harmful lifestyle patterns like 3 p.m. sleep, late meetings, morning and evening physical activities, etc.

5.2. Machine Learning Algorithms Used

We used mainly tree-based and regression algorithms as they are known for their ease of interpreting results, which is a key aspect for the acceptance of the results by physicians. Random Forest, Gradient Boosting, and Extra Trees classifiers as well as Stochastic Gradient Descent and Support Vector Machines were used for classification. Random Forest and Gradient Boosting regressors were used for prediction tasks. Hyperparameter configurations

were optimized on validation data using nested cross-validation, where the parameters of the models were optimized on the inner loop, and the performance of the chosen model was estimated on the outer loop. We also set additional parameters for the optimization and evaluation of our models to those provided for the classification model and metrics functions.
For the two-step classification based on metabolism data, first the best class variable was sought by studying the relation between all the blood tests and the characteristics of the candidates. The best discriminant algorithm was then used with the selected variable. We often used classifiers in the form of a simple single tree to study how these blood test variables correlated with the best class and to present the relevant associations as simply as possible. The best derivative class variable was sought by studying the relation between all the blood tests and the rate of change of ISC for classification based on derivative nights of wear in the week preceding the blood test. Random Forest is the best algorithm for the night class. The best deriv_nights class variable was sought by studying the relation between all the blood tests and the rate of change of the ISC for a fixed differentiating week for classification based on the nights of wear in the week preceding days.

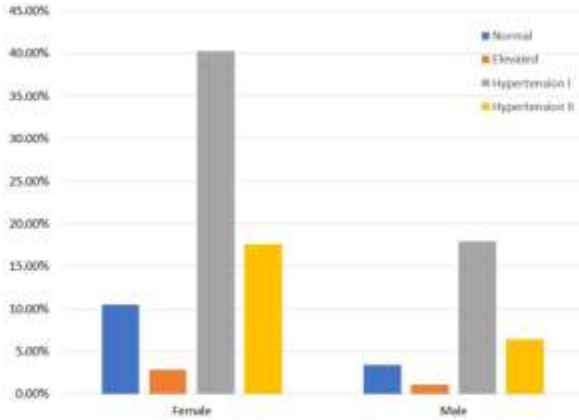

Fig 7: Cardiovascular Diseases Risk Prediction

5.3. Case Studies

Case 1. Corporate Employees. It is getting ever harder to combine a high-paid and satisfying career with a healthy and harmonious lifestyle. The pressures of daily life, career demands, long and busy workdays, and extensive business travel schedules often lead to metabolic stress, especially if combined with inadequate daily rhythms and poor dietary habits. That is why we decided to implement the promised diagnostics before healthcare departments of our corporate clients. As expected, the deviation was observed. Analyzing their lifestyle and daily rhythms, we organized our recommendations for optimizing an individual plan. The demonstrated health potential speaks volumes about the feasibility of Lifestyle programs.
Case 2. University Students. During their study years, students begin to form their professional lifestyle. Depending on their future professions, for future students of the dental and medical faculties, compliance with lifestyle optimality rates, on the one hand, can become particularly challenging. On the other hand, it is not only the knowledge acquisition that will fill their emotional intelligibility. Active participation and feeling great every day are important too. Such data and the result are shown for the first semester master level of one of the university descendants.

6. CHALLENGES AND ETHICAL CONSIDERATIONS

The AI-driven data analysis forms a part of a broader issue space surrounding the research and development conducted on the border between technological progress and human welfare.

Thus, it is imperative to critically consider both the scientific challenges and the ethical issues accompanying these technological innovations throughout the entire project to integrate scientific and technical expertise, including the knowledge acquired on deep learning at the project front line, into an interdisciplinary research framework that embeds ethical issues—both in terms of the relational dimension and individuals' well-being. Furthermore, great responsibility comes with the zeal of embracing innovation in research in order to ensure that the trends in lifestyle data for early detection of metabolic disorders are compliant with privacy and data protection policies and legislation. Throughout the project, ethical issues have been proactively addressed, and several processes are implemented to ensure ethical compliance. Personal data protection measures were adopted throughout all data collection stages according to the EU level of data protection regulation.

The face and name of the volunteers are rendered unrecognizable, and volunteers' facial traits are anonymized, for example, by effectively anonymizing facial data to comply with the new privacy regulation. The consent form also specifies that study data and study models will be stored in a secure IT environment and will be used for the advancement of scientific knowledge, as well as for drafting scientific publications and reports, but not for discussion of the findings in the publication and/or materials. Before any sharing of the stored processed data, the data or any updates are sent to the ethics committee for approval. After signing an informed consent form, an encrypted personal contact email address is requested to periodically contact the volunteers during the course of the trial, thus enhancing connectivity with the often disadvantaged target population. Ethical and privacy issues were also carefully addressed with the structured interviews carried out with health professionals. This was designed to make people more comfortable with the study and the work of the research team. Interviewers respond to each concern by highlighting that the interview (and the lifestyle analysis encoded in the software, once completed) is useful for data analysis aimed at improving the health status of citizens, as well as for discussing the software for the prevention of metabolic syndrome in clinical practice.

$$P_e = \begin{cases} 1 & \text{if } R_d \geq T \\ 0 & \text{if } R_d < T \end{cases}$$

P_e: Early detection outcome (1 = detected, 0 = not detected).

R_d: Risk score for metabolic disorder.

T: Detection threshold.

Equation 3: Early Detection Threshold Model

6.1. Data Privacy and Security

In this publication, we demonstrate the practical utility of a privacy-compliant federated learning model to predict patterns in biome data associated with potential contributors to T2D and CVD risk. Notably, this includes conducting model training and inference on three independent datasets in a manner that allows for data to remain on their local devices, avoiding direct exposure of individual records. Federated learning and a privacy-preserving protocol significantly improve the model's scalability and reduce information security risks compared with existing predictive machine learning or neural network models. Given existing concerns with AI and privacy, notably the theft and misuse of personal data, our privacy-preserving model has the potential to dramatically improve the utility of AI models for personalized health and to facilitate locoregional data management. This technology can be extended to other models and applications by other researchers and industry partners to improve data security, reduce connection risk, and more effectively address privacy concerns associated with data analyses based on individual subscription services.

Difficulties and security challenges can be overcome by adopting a range of federated learning security measures that can be applied at the data, training, and model stages. In conjunction with model results discussed herein, we guarantee the efficacy of our measures by sharing all privacy-compliance techniques that were applied, along with the existing limitations, in an effort to advance privacy-concerned AI models currently limited by the needs of app vendors, benefits of data analytics, and requirements and reasons that contribute to the delay of potential health applications that hold promise for improving individual lifestyle and for providing essential feedback for populations.

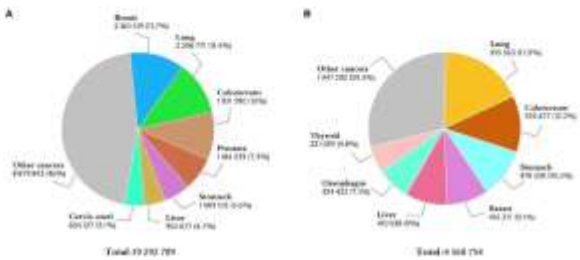

Fig 8: Application of artificial intelligence in diagnosis and treatment of colorectal cancer

6.2. Bias and Fairness in AIa

The issue of fairness in machine learning systems has recently attracted significant attention due to potentially negative repercussions various biases can have in areas like criminal justice and healthcare. Moreover, awareness of ethical issues and responsible AI development surged through well-publicized incidents of biased AI.

In medicine, fairness is often affected by existing biases in medical data, processes, and decision-making. IMRS are learning from multimodal feature vectors, which are built from multimodal sensors. Thus, interventions to create fair models may span any step, deriving the online sensor used to capture lifestyle data, during the human computation process for the annotation of multimodal sensor data or on the multimodal sensor feature vectors. Metadata and auxiliary data, including the labels and/or demographic information, can be used to induce fairness constraints. Nonetheless, our technique is intended to provide a structured way of assessing model fairness even in scenarios where only the label and test outcome are available. We would advise careful analysis of input features if this were to be used.

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