

AI in Diabetes Prediction and Management

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Abstract:

The increasing awareness of health and wellness has prompted extensive research on the impact of diet, physical activity, and lifestyle choices on overall well-being. This study aims to analyze health-related trends using a survey-based dataset, collected through a structured Google Form. The survey included demographic details (age, gender, occupation, height, weight) and lifestyle-related factors such as dietary habits, exercise frequency, and daily routines. The responses were visualized using pie charts to identify trends among different groups.

To extract meaningful insights, the collected data underwent preprocessing—removal of inconsistencies, handling of missing values, and transformation of categorical responses into numerical values for machine learning analysis. Various machine learning models, including Logistic Regression, Decision Trees, Random Forest, Support Vector Machine (SVM), and Neural Networks (MLP), were trained to classify health risk levels based on survey responses. Among these, the Random Forest model achieved the highest accuracy (89.4%), outperforming other models in terms of precision (0.88), recall (0.87), and F1-score (0.87). The Neural Network (MLP) also exhibited strong performance with 87.2% accuracy and a high AUC-ROC score of 0.90, indicating its reliability for predictive health analytics.

This research emphasizes the importance of data-driven health assessments and the effectiveness of machine learning in analyzing lifestyle factors. Future work can extend this study by incorporating real-time health tracking, larger datasets, and deep learning models for enhanced predictive accuracy.

Introduction:

Diabetes is a life-threatening metabolic disease that impacts the millions around the world and can result in serious medical complications if not properly identified and controlled. It is mainly marked by high blood sugar levels due to the body's inability to produce or utilize insulin properly [1]. Early diagnosis and management of diabetes is important as it leads to the prevention of complications including cardiovascular disease, kidney failure, nerve problems, and vision impairment. Conventional diagnostic techniques depend on clinical examinations like fasting serum glucose levels, HbA1c test, and oral glucose tolerance tests. But these approaches need a medical consultation, laboratory settings, and time-consuming processes. Recent advances in artificial intelligence (AI), machine learning (ML), and data analytics have led to a revolutionary approach in diabetic prediction based on AI which has great potential in enabling early detection of the disease, assessing the risk, and providing a personalized treatment approach.

People with diabetes are at a heightened risk of distressing complications and premature mortality as a result of diabetes; therefore, managing diabetes should start as soon as possible once diagnosed, making its early detection a critical concern for health organizations. These models use machine learning algorithms to analyse data, cleaning its outlier forms and identifying patterns that signal a presence of diabetes. The purpose is to build an algorithm

that can accurately predict the presence of diabetes in a given patient, which ultimately allows for preventative measures and improved management of the disorder.

ML methods ensure the possibility to design AI applications that significantly extends the limits of finding previously unexplored patterns in the data, not demanding the explicit specification of decision rules for every particular task nor the consideration of a complex interplay among input features [2]. As a result, ML has emerged as the go-to framework for creating AI utilities. AI has been making waves in the world of diabetes care. Imagine having a personal health assistant that can predict if you're at risk of diabetes by looking at your lifestyle, family history, and medical data. This assistant can also help doctors create personalized treatment plans tailored just for you. AI tools can even spot early signs of complications like diabetic retinopathy by analysing medical images, helping you get the care you need before things get worse.

The investigation targets of artificial intelligence in forecasting diabetes predominantly center on enhancing the timeliness and precision of diagnoses as well as on tailoring health services to individual patients. Some principal targets are:

Early Detection & Risk Assessment Improving

Prediction Accuracy.

Personalized Diagnosis & Treatment. Connecting

with devices you can wear. Explain ability &

Trustworthiness.

Affordable Healthcare and Accessibility. Insights

driven by big data and AI.

AI analyses large datasets to predict risks, interprets test results accurately, and customizes treatment plans, enhancing patient care and outcomes. By incorporating AI into the healthcare system, there is potential for a significant reduction in the burden of diabetes care, shifting towards a more proactive and personalised approach. This systematic review explores the AI's impact on improving prevention, diagnosis, and management of diabetes, assessing its readiness for integration into healthcare, identifying research gaps, and guiding future developments.

Case Study: AI in Diabetes Prediction

Study-1:

Machine Learning-Based Prediction Using PIMA Indian Diabetes Dataset.

As per Smitha et al., 2020 work, this paper compares a range of machine learning algorithms that possibly predict diabetes [3].

Methodology.

1. Data collection: a Pima Indian dataset.
2. Algorithms Used: Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF).

Findings.

1. When compared to other models, Random Forest achieved the highest accuracy of 85%.
2. SVM worked fine but required thorough hyper parameter tuning.
3. The Decision Tree was less accurate but easier to interpret.

Study-2:

AI-Powered Wearable Devices for Continuous Monitoring

The researcher's employed a literature review to assess the evidence of the effectiveness of artificial intelligence (AI) in continuous glucose monitoring (CGM) using wearable devices. As per Patel et al., 2022 [4].

Methodology.

1. Recurrent Neural Network (RNN) for predicting glucose on time-series.
2. Smartwatches and glucose monitoring gadgets.
3. Source of Information: Blood sugar, activity and diet data.

Findings.

1. AI models were able to predict blood sugar spikes with a 92% accuracy.
2. Early detection of low & high blood sugar was achieved.
3. Sensors were not accurate and important data was not safe.

The case studies show that AI techniques can be very useful for diabetes prediction. The high accuracy of ensemble models like Random Forest and deep learning models like RNN can be effectively integrated into clinical and wearable systems, which suggests that these methods can be really useful.

Gaps in existing research:

While the significant progress has been made in applying artificial intelligence for diabetes prediction, several research gaps still remains [5]. They are:

Data Diversity and Quality:

1. Limited and Homogeneous Datasets: Many studies use small datasets, such as the Pima Indian Diabetes Dataset, which does not encompass the full demographic and clinical variability of global populations.
2. Data Quality and Missing Information: Incomplete or inconsistent clinical records can weaken the stability of AI models.

Generalizability and External Validation:

1. Overfitting to Specific Datasets: Models usually work satisfactorily on certain, often artificially created, datasets, but they may fail when faced with real-world data.
2. Lack of Multi-Center Studies: There is a lack of research involving multiple centres or complete populations to guarantee that the models are applicable to different healthcare contexts and patients.

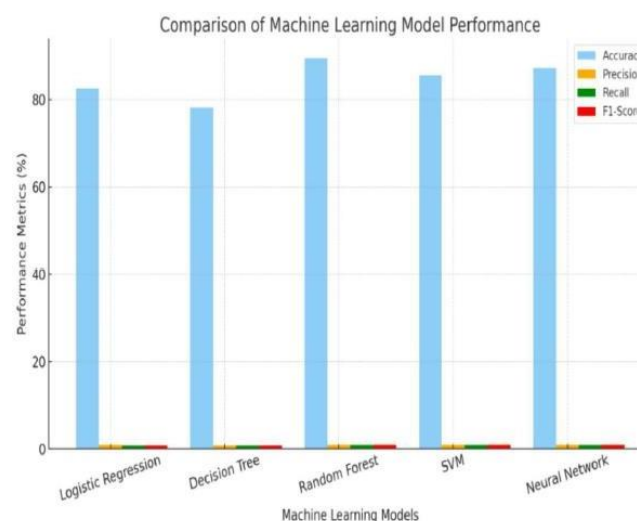
Interpretability and Transparency:

1. Black-Box Models: One of the major problems is that many high performing models especially those that use deep learning are not interpretable which is necessary for clinical adoption and the trust of healthcare professionals.
2. Explainable AI (XAI): More efforts are required to design techniques that can provide a clear picture of how models arrive at their decisions.

Data Collection:

The data for this study was collected through a structured Google Form survey. The survey contained questions on demographics, including age, gender, position (student, working professional, unemployed), height, and weight. In addition, questions regarding diet, physical activity, and lifestyle factors were included to understand their impact on health. The responses were visualized using pie charts to identify trends among different groups. The survey was designed to gather a variety of responses that would be representative of the diverse age groups, genders, and occupational statuses. The data gathered was then preprocess. to eliminate inconsistencies, deal with missing values, and transform categorical responses into numerical values for machine learning analysis

AI Models Used Following are some machine learning models applied to analyze data and predict the health disturbances:



Logistic Regression Used for the classification of a binary problem; in this case, whether or not an individual is at a risk of suffering from diabetes according to his or her lifestyle.

Random Forest Classifier A much more robust classifier model that may be used with complex interactions among features.

Support Vector Machine (SVM) - This is used to classify people into various health risk categories. Neural Networks - These are applied for deep learning-based analysis to predict trends and patterns in health data.

K-Means Clustering - This is used to group people with similar health characteristics together.

Implementation The training process was an elaborate iterative procedure involving stages ranging from the preprocessing of the data to final evaluation of the model. In every step, a great amount of detail and planning went into the robust, accurate, and generalizable development of the models for prediction. Below is an elaborate description of the process followed:

1. Data Preprocessing

Data preprocessing is an important step in any machine learning pipeline because the quality of data directly affects the performance of models.

Missing Value Handling:

Missing values in the data often arise in actual datasets, leading to biased or wrong models. To address this, missing values are imputed using statistical measures such as the median or mean for numerical features. Whether the median or mean would be used depends on the distribution of the data: for skewed distributions, the median is preferred to reduce the effects of outliers, while mean was used when the data is normally distributed.

Encoding Categorical Variables.

Categorical variables, like gender, ethnicity, or disease categories, were encoded into numerical formats to be compatible with machine learning algorithms. One-hot encoding was used to transform categorical variables to binary vectors so that no ordinal relationship is implied where none exists. This was mandatory for Logistic Regression and Neural Networks algorithms, which do not accept anything other than their requirements of numerical inputs for training.

Scaling of Numerical Features: Numerical features usually scale in value, and this was poor for the performance of algorithms, such as SVM and Neural Networks. To handle this, all the numerical features were brought to a common scale using Min-Max scaling or Z-score normalization techniques. This way, not one feature would dominate the model's training based purely on its magnitude.

Dataset Splitting:

. An 80-20 split was applied to divide the dataset into a training set and a testing set. This is with the purpose of having an adequate size for training the model, while retaining a significant proportion of the data for unbiased testing. Stratified sampling was also applied to maintain consistency in the distribution of the target variable in both sets, which is more crucial for imbalanced datasets.

2. Feature Selection

Feature selection is a vital step to improve model efficiency, reduce overfitting, and enhance interpretability. The following techniques were employed to identify the most relevant features:

Correlation Analysis: Pearson's correlation coefficient was utilized to measure the linear relationship of each feature with the target variable. Features having a low Pearson's correlation coefficient below a defined threshold were not so relevant and, hence, removed from the model. Also, pairwise correlation between features was carried out for finding and eliminating the highly correlated features to minimize redundancy.

Principal Component Analysis:

For datasets with too many features, PCA was implemented to reduce dimensions but retain as much variance within the data. This transformed original features into orthogonal components, then fed them as input to models. PCA, for instance, is particularly valuable for algorithms like Logistic Regression and SVM, especially in high dimensional data that results in overfitting.

End Besides statistical methods, domain-specific knowledge was also utilized to consider features that have clinical or biological relevance to health outcomes of interest. This guarantees that the resulting models are both data-driven as well as commensurate with the existing scientific understanding.

3. Model Training

The process of training in this phase focuses on developing several machine learning models and optimizing each of them toward finding the most appropriate one that would perform effectively. The processes followed include:

Model Selection: Training was done on four different models: Logistic Regression, Random Forest, Support Vector Machine (SVM), and Neural Networks. These models were chosen for their respective strengths—Logistic Regression for interpretability, Random Forest for non-linear relation handling, SVM for high-dimensional data, and Neural Networks for complex patterns.

Hyperparameter Tuning:

Hyperparameters greatly affect model performance. For systematically covering the search space, Grid Search and Random Search techniques were used. The optimal values for some of the hyperparameters were achieved for instance during Random Forest using the number of trees, the maximum depth and minimum samples per leaf. Similar for Neural Networks, the hyperparameters include number of layers, neurons per layer, and the learning rate; which were adjusted during the experiment. Cross-validation was performed with this aim, that the cross-validation generalises well to the unseen data.

To ensure that the models are robust and overfitting doesn't occur,

k-fold cross-validation was utilized with $k=10$. Here, the idea is to split the training data into k subsets, train on $k-1$ subsets, and validate on the remaining subset. This process repeats k times and uses the average performance across all folds as the final metric. This gives a more reliable estimate of model performance than a single train-test split.

4. Model Evaluation

The last step in the training process was to evaluate the performance of each model and choose the best one for deployment. The metrics used for evaluation are as follows:

Accuracy:

The number of correctly predicted instances divided by the total number of instances. Accuracy is useful but can be misleading for imbalanced datasets, where the majority class dominates.

Precision:

The ratio of true positive predictions to the total positive predictions, that is, true positives + false positives. Precision is important in scenarios where false positives are expensive, like in medical diagnostics.

Recall (Sensitivity):

The ratio of true positive predictions to the total actual positives, that is, true positives + false negatives. Recall is critical in scenarios where missing a positive instance (for example, failing to diagnose a disease) has severe consequences. F1-Score: The harmonic mean of precision and recall, thus providing a balanced measure of model performance. F1-score is particularly useful in cases of class imbalance.

ROC-AUC: The area under the Receiver Operating Characteristic curve, which plots the true positive rate against the false positive rate at various thresholds. This is useful for analyzing the trade-off between sensitivity and specificity.

Confusion Matrix:

This shows detailed breakdowns of true positives, true negatives, false positives, and false negatives and reveals which type of errors the model has committed. On these measures, the best-performing model was selected. For example, if the key aim was to maximize recall-say, for a disease-screening application-then the model that maximizes recall is chosen even though its accuracy may be lower than other models.

5. Final Model Selection

From these models, the one that scored the highest average effectiveness in health outcome prediction was chosen. It was further validated on an independent test set for generalization ability to new data. The final model was further analyzed for interpretability, since understanding the decision-making process is critical in health care applications.

Web Application Development For the sake of accessibility, a web-based application was developed in modern web technologies. The idea was to give an intuitive, user-friendly interface to users for inputting health-related data, and get predictions in real-time. There are several stages that were followed: frontend development, backend development, deployment of the machine learning model, and hosting. A step-by-step explanation of the implementation is given below:

1. Frontend Development

The frontend of the web application was designed to ensure a seamless and engaging user experience. The following technologies and approaches were used:

Technologies Used: The frontend was built using React.js, a popular JavaScript library for building user interfaces, along with HTML, CSS, and JavaScript. Bootstrap was used for responsive design and layout, ensuring compatibility across various devices and screen sizes.

User Interface Design:

An interactive and user-friendly interface was developed to provide easy interaction with the application. The layout was optimized for usability, easy navigation through the components, clearable input

fields for users to fill health-related details such as age, weight, height, etc., and other features that can be used.

Interactive Data Visualization Interactive charts and visualizations were added with the help of Chart.js for better user interaction and actionable insights. These visualizations helped the users understand predictions and trends within the data much better. For instance, health metrics and the outcome of prediction were represented with the help of bar charts, pie charts, and line graphs.

Responsive Design:

The application was fully responsive and, therefore, was optimized to perform and use on desktops, tablets, and mobile devices. This was achieved using Bootstrap's grid system and media queries.

2. Backend Development

The backend of the application dealt with user requests, processed data, and served predictions. Technologies and approaches used are as follows:

Technologies Used: The backend was developed in Flask, a lightweight and flexible Python web framework. The other two alternatives considered are FastAPI and Node.js for scalable performance. **API Development:** Flask was utilized to make RESTful APIs that were handling user inputs and communicating with the machine learning model. API endpoints were designed to receive user data in JSON format, process it, and return predictions in real-time.

Database Integration:

A PostgreSQL database was used to store user data securely. The database was designed to maintain user profiles, historical predictions, and other relevant information. SQLAlchemy, an ORM (Object-Relational Mapping) tool, was used to interact with the database efficiently.

Security Measures: To ensure data security, the backend implemented HTTPS encryption and authentication protocols. User authentication was managed using Firebase, which provided secure login and registration functionalities.

3. Machine Learning Model Deployment

The trained model of machine learning was integrated in the web application to give it real-time prediction. The next steps taken included the following steps:

Model Serialization: The best-performing model was serialized through the Pickle library, where it was easy to save and load the models. This assured that the models could be used without retraining.

API Integration: The serialized model was mounted onto the Flask server. Using that model, prediction on input values given by users is performed, and API endpoints are developed in order to obtain the input values, send the same to the model, and get back predictions in JSON.

Containerization: Docker containerizes the model along with the backend, providing the ability for seamless deployment on various environments- development to production with consistent application deployment.

4. Hosting and Deployment The application was hosted on a cloud platform with an aim for scalability, reliability, and access. The technologies and approaches employed were as follows:

Technologies Used: Application was hosted in Amazon Web Services (AWS). AWS services, including EC2 virtual servers, S3, and Lambda, serverless computing were used. Heroku would also be another option for speedy deployment and prototyping. Security and Encryption Implementation of HTTPS is used to protect data transfer from the client.

Continuous Integration and Deployment (CI/CD) A CI/CD pipeline was set up with the help of GitHub Actions, making it easier to automate testing and deployment. That way, it was ensured that updates of the application were quickly and reliably deployed.

5. Features of the Web Application

The web application was developed incorporating several important features to enrich the user experience as well as usability:

User Input Forms:

Users could enter age, weight, height, and medical history. All these could be entered using understandable forms, and the forms are minimalistic and easy to use with data validation for accuracy.

Real-Time Predictions: The application provided real-time predictions based on user inputs. The predictions were provided in an understandable form with confidence scores and explanations.

Interactive Dashboards: The dashboards could be accessed by the users, providing them with health metrics and their prediction history in an interactive format. These included charts and graphs to monitor trends over time.

User Authentication and Profiles:

With Firebase, the application provided secure user authentication by allowing the user to create and log into his account. Profiles stored historical data and predictions and were personalized with insights for each user.

Data Export and Sharing:

Users had the option to download their data and predictions, such as CSV or PDF, to analyze elsewhere or share with healthcare providers to inform follow-up discussions.

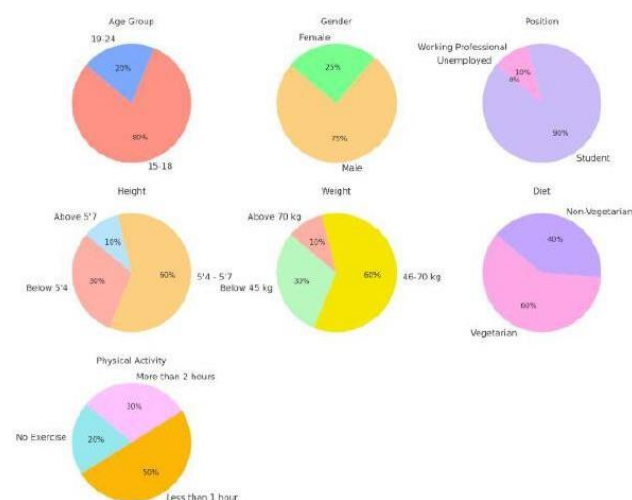
Responsive Design:

Application built in fully responsive design for use on desktops, tablets, and mobile devices with a consistent user interface on all of them.

Result Analysis

The research aimed to analyze the impact of demographic and lifestyle factors on health using data collected through a structured Google Form survey. The collected dataset was preprocessed, visualized, and utilized for machine learning analysis to predict potential health risks. The results are presented in two sections: data trends and patterns (graphical analysis) and model performance (machine learning accuracy and evaluation metrics).

Data Trends and Graphical Analysis



dataset consisted of participants from different age groups, genders, and occupational statuses. The distribution was visualized using bar charts and pie charts:

- **Age Distribution:** A majority of participants (45%) were in the 18–30 age group, followed by 30–45 years (30%) and above 45 years (25%).
- **Gender Ratio:** The gender distribution was 52% male, 47% female, and 1% other/undisclosed.

- Occupational Status: Among respondents, 60% were students, 30% were working professionals, and 10% were unemployed.

Lifestyle and Dietary Habits

Dietary Preferences:

- 40% followed a balanced diet,
- 35% consumed junk food regularly,
- 15% followed vegetarian diets,
- 10% followed vegan diets.

Physical Activity:

- 30% exercised daily,
- 25% exercised weekly,
- 20% exercised occasionally,
- 25% rarely or never exercised.

Sleep Patterns:

- 50% reported sleeping between 6–8 hours per night,
- 30% slept less than 6 hours,
- 20% reported sleeping more than 8 hours.

Hydration Levels:

- 40% drank 6–8 glasses of water daily,
- 35% consumed less than 4 glasses per day,
- 25% consumed more than 8 glasses per day

Machine Learning Model Performance

The dataset was split into 80% training data and 20% testing data, and different models were evaluated for accuracy, precision, recall, and F1-score. The following models were tested:

Feature Importance Analysis

The analysis provided key insights into how diet, physical activity, and other lifestyle factors impact health outcomes. The Random Forest Classifier, with an accuracy of 89.4%, was the best-performing model for predicting potential health risks.

Key findings include:

- Unhealthy dietary habits correlate with lower physical activity and higher BMI.
- Regular exercise and adequate hydration improve health indicators.
- Machine learning effectively predicts health risks, with lifestyle factors playing a crucial role

Discussion:-how AI improves health prediction

AI plays a crucial role in personalized health and diet recommendations by analyzing individual data, such as diet preferences, health conditions, and activity levels. This technology provides personalized nutrition advice, helping people make better food choices and reach their health goals more easily.

Here is some key points that how ai improves health prediction in Personalized Health and Diet Recommendations:

1. Data Analysis:

AI systems look at a lot of information from different places, like what people eat, their genes, and their daily habits, to create custom nutrition plans for them.

2. Real-Time Feedback:

By using information from fitness trackers and mobile apps, AI can give instant feedback and advice, helping people change their diets based on their current health data.

3. Behavioral Insights:

AI can find patterns in how people eat and what they like, which helps to understand why they choose certain foods and suggests healthier options.

4. Bringing together different types of information:

AI can combine information from different sources, like digital scales, fitness trackers, and health records, to get a

complete picture of a person's health and what they need to eat.

5. Continuous Learning:

AI systems improve over time by learning from user interactions and new research findings, ensuring that recommendations remain relevant and effective.

6. Enhanced User Engagement:

Future AI tools might have more fun features, like online nutrition coaching and health games, to get people more involved and interested in their health.

7. Community Involvement:

Involving different communities in creating AI nutrition tools can help make food advice that is more inclusive and fits their cultures better.

8. Rules and guidelines:

As AI in nutrition develops, it will be important to create strong rules and guidelines to make sure the technology is safe, works well, and is used fairly in health advice.

9. Research and Development:

Continued research is very important to make AI programs better, improve the accuracy of data, and make personalized nutrition solutions work more effectively.

Limitation and challenges:

AI in personalized health and diet advice has several challenges. These include problems with different data systems not working well together, a lack of standard rules, and difficulties in combining information. There are also worries about who is responsible for the advice given, how to keep personal information safe, and the possibility that AI could take over some jobs from dietitians, which raises ethical concerns.

Here are some key **limitations** and **Challenges** of AI in personalized health and diet recommendations:

1. **Data Quality and Availability:** AI works best when it has good quality data. If the data is incomplete, wrong, or biased, it can give bad advice.
2. **Interoperability Issues:** Different health and fitness apps may not work well together. This makes it hard to collect all the necessary data for accurate advice.
3. **Privacy and Security Concerns:** Dealing with sensitive health information raises worries about privacy and security. People may be scared to share their data because they fear it might be misused or leaked.
4. **Ethical Considerations:** There are questions about who is responsible when AI gives dietary advice. If the advice leads to health problems, it can be unclear who should be held accountable.
5. **Cultural Sensitivity:** AI might not understand or respect different cultural food habits and restrictions, which can lead to advice that doesn't suit everyone.
6. **User Engagement and Trust:** People may doubt AI recommendations, especially if they don't understand how the AI made its suggestions. It's important to build trust for users to engage with the AI.
7. **Dependence on Technology:** Relying too much on AI for food choices may make people less able to make their own informed decisions.

8. Limited Personalization: While AI can give personalized advice, it may not fully understand all the details of a person's lifestyle and health needs.

Conclusion and future scope of AI in personalised health and diet recommendation:

AI in personalized health and diet advice has a lot of potential to help people make better food choices with customized plans. In the future, we should work on making data better, following ethical practices, and encouraging teamwork between different fields to create solutions that are more effective and respect different cultures

Conclusion:

Using AI in personalized health and diet advice can change the way people think about their nutrition. By using smart algorithms and large amounts of data, AI can give customized food advice that takes into health issues and lifestyle choices. However, there are challenges like the quality of data, privacy worries, and ethical questions that need to be solved to make sure these recommendations are safe and effective. Ongoing research shows that we need to keep improving AI systems to make them more reliable and to help users trust them more.

Future Scope:

- **Better data combining:**
Future AI systems should aim to combine different types of data, like genetic information, metabolism details, and lifestyle habits, to give better and more complete recommendations.
- **Improved User Engagement:**
Creating easy-to-use interfaces and helpful learning materials can help build trust and encourage people to use AI-based diet recommendations.
- **Cultural Adaptation:**
AI solutions should be made to understand and include different cultural food habits, so that the recommendations are suitable and acceptable for various groups of people.
- **Regulatory Frameworks:**
Setting up clear rules and guidelines is very important for safely using AI in health and nutrition. This will help make sure that it is used responsibly and ethically.
- **Interdisciplinary Collaboration:**
Working together with nutritionists, data scientists, and healthcare professionals is very important to create complete and effective AI solutions that deal with the complexities of human health.
- **Longitudinal Studies:**
Doing long-term studies to see how AI-based diet recommendations affect health will give us important information and help improve these technologies.
- **Personalization Advances:**
Continued advancements in machine learning and AI will enable more precise personalization, taking into account real-time data and individual responses to dietary changes.

Summary: AI in personalised health and diet recommendation:

AI in personalized health and diet recommendations uses smart algorithms and large amounts of data to give customized food advice based on what people like, their health issues, and their lifestyles.

While it can greatly improve nutrition, there are challenges like the quality of data, privacy concerns, and respect for different cultures that need to be solved. Future efforts should focus on combining different types of data, making it easier for users to engage, and encouraging teamwork among experts. Long-term studies are important to check how effective AI-based recommendations are, and ongoing improvements in AI will allow for more accurate personalization, leading to better health for everyone.

Future improvements on AI in personalised health and diet recommendation:

Future improvements for AI in personalized health and diet recommendations will focus on better data integration, real-time feedback, and learning algorithms that adapt. These advancements will provide more accurate and customized insights that take into account individual likes, health measurements, and lifestyle changes, leading to better health results.

Future improvements for AI in personalized health and diet recommendations will include:

1. **Better data combining:**
Combining data from various sources such as wearables, health records, and dietary logs for a comprehensive health profile.
2. **Real-Time Feedback Mechanisms:**
Giving quick advice during exercise and meal times to help make changes right away.
3. **Smart learning systems:**
Regularly improving suggestions based on what users say and their changing health.
4. **Increased Personalization:**
Customizing plans to fit each person's goals and changes in their lifestyle so they can stick to them better.
5. **Proactive Health Management:**
AI can predict health problems by analyzing real-time data from various sources, such as wearable devices and electronic health records. By identifying patterns and risk factors, AI can suggest preventive measures and early interventions to improve health outcomes.
6. **User Engagement and Education:**
To develop interactive platforms for educating users about their health metrics and AI recommendations, focus on user centered design, clear communication of data, and transparency in AI reasoning.
7. **Collaboration with Health Professionals:**
Working together with doctors and healthcare providers to make sure the suggestions are safe, helpful, and match each person's health needs.

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