

DEVELOPMENT OF A MOBILE APP FOR PERSONALIZED NUTRITION PLANNING USING DEEP LEARNING MODELS

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Abstract: In the evolving field of personalized nutrition, mobile applications equipped with advanced technologies are increasingly important for delivering tailored dietary advice. This paper explores the development of a mobile app that leverages deep learning models to provide personalized nutrition planning. The app integrates user-specific health data, including age, gender, activity level, and health conditions, to generate customized dietary recommendations. By employing neural networks and other deep learning techniques, the app aims to enhance the accuracy and relevance of nutrition advice, addressing the limitations of generic dietary suggestions. The development process involved data collection from various sources, model training, and app design to ensure a user-friendly interface and real-time feedback. Evaluation through user testing demonstrated the app's effectiveness in improving dietary adherence and user satisfaction. The results underscore the potential of deep learning to revolutionize personalized nutrition by offering precise and actionable recommendations. This research contributes to the growing body of knowledge on mobile health technologies and their application in personalized dietary interventions, highlighting future directions for enhancing app functionality and expanding its impact on user health outcomes.

Keywords: Personalized Nutrition, Dietary Recommendations, Neural Networks, Health Data, User Interface, Mobile Health Technologies, Dietary Adherence.

I. Introduction

In recent years, the pursuit of optimal health has increasingly shifted towards personalized approaches that cater to individual needs and preferences. Traditional dietary recommendations, often generalized and one-size-fits-all, have struggled to address the unique health profiles and nutritional needs of diverse populations [1]. This gap in personalized dietary planning has prompted significant interest in leveraging advanced technologies to provide tailored nutritional guidance. Among these technologies, mobile applications have emerged as powerful tools for health management, offering users convenience and real-time access to personalized health solutions. The integration of deep learning models into mobile applications represents a promising advancement in personalized nutrition [2]. Deep learning, a subset of machine learning, involves the use of artificial neural networks to analyze complex patterns in large datasets. By harnessing these models, it is possible to process intricate health information and generate highly individualized dietary recommendations. Unlike traditional methods that rely on static guidelines, deep learning models can adapt to users' evolving health data, preferences, and lifestyle changes, thereby enhancing the precision and relevance of dietary advice [3]. The development of a mobile app that employs deep learning for personalized nutrition planning aims to address the limitations of conventional dietary recommendations. The app leverages user-specific data such as age, gender, activity level, and existing health conditions to tailor dietary suggestions. This individualized approach not only improves the accuracy of recommendations but also aligns them more closely with users' unique health goals and nutritional needs [4]. The app's design incorporates an intuitive user interface, ensuring that complex algorithms are translated into accessible and actionable advice for users. One of the key motivations behind developing such an app is the increasing demand for personalized health solutions [5]. As individuals become more proactive in managing their health, there is a growing expectation for tools that provide customized guidance rather than generic recommendations. Mobile apps, with their widespread adoption and capability for continuous interaction, offer an ideal platform for delivering these personalized solutions. By integrating deep learning models, the app can analyze large volumes of data, identify patterns, and generate tailored recommendations that adapt to users' changing needs [6]. The app's development process involves several critical steps, including data collection, model training, and user interface design. Data collection encompasses gathering diverse nutritional and health-related information, which is then used to train deep learning models. These models are designed to analyze the data and predict personalized dietary recommendations based on users' profiles [7]. The app's user interface is crafted to facilitate easy interaction, ensuring that users can effortlessly access and implement the personalized advice provided. User testing is a crucial component of the app's development, providing insights into its effectiveness and usability. Feedback from users helps refine the app's functionality, improve the accuracy of recommendations, and enhance the overall user experience. The positive outcomes observed in initial testing highlight the potential of deep learning models to transform personalized nutrition planning and support healthier dietary choices [8]. The development of a mobile app for personalized nutrition planning using deep learning models represents a significant advancement in health technology. By offering tailored dietary recommendations that adapt to individual needs, the app addresses the limitations of traditional approaches and meets the growing demand for personalized health solutions [9]. This research not only contributes to the field of mobile health technologies but also sets the stage for future innovations in personalized nutrition and health management.

II. Literature Survey

The literature on integrating technology with nutrition and language processing highlights significant advancements and applications across various methodologies and domains. eHealth technologies have been shown to support dietary and physical activity behaviors, particularly in individuals managing diabetes, by enhancing self-management and health outcomes [10]. Assessments of popular nutrition-related mobile apps reveal the need for reliable and accurate tools to provide effective dietary guidance. In language processing, convolutional neural networks (CNNs) have been employed to understand and interpret spoken meal descriptions, as well as to map natural language input to database entries. Advances in deep learning methods for language understanding and semantic analysis further contribute to this field [12]. Foundational work on CNNs for image recognition has significantly improved the accuracy and efficiency of image classification tasks, including specialized applications like food image recognition. Integrating CNNs for natural language processing tasks and employing character-based embedding models have enhanced language understanding systems, particularly in the context of nutrition [13]. The transformative impact of deep convolutional neural networks on image classification has influenced subsequent research and applications, reflecting the continuous evolution and potential of technology in improving nutrition management and related fields [14].

Author & Year	**Area**	**Methodology**	**Key Findings**	**Challenges**	**Pros**	**Cons**	**Application**
Rollo et al., 2016	eHealth Technologies	Review of digital tools	Ehealth tools improve self-management in diabetes; can enhance dietary and physical activity behaviors.	Variability in tool effectiveness	Enhances self-management	Limited by tool effectiveness and user engagement	Diabetes self-management
Fallaize et al., 2019	Nutrition Apps	Assessment against UK reference methods	Popular nutrition apps show varying degrees of reliability; highlights need for standard evaluation criteria.	Limited app consistency and accuracy	Provides insights into app reliability	Accuracy varies among apps	Nutrition guidance and monitoring
Korpusik et al.,	Language Processi	Distributional	Effective use of distributi	Requires large	Advances understanding of	May struggle with varied	Meal description

2016	ng	semantics	onal semantics for understanding spoken meal descriptions.	datasets	meal descriptions	language inputs	interpretation
Korpusik et al., 2017	Language Processing	Semantic mapping using CNNs	CNNs can map natural language input to structured database entries effectively.	Complex mapping processes	Improves data entry accuracy and understanding	Dependency on high-quality data and models	Structured data entry for meal descriptions
Korpusik et al., 2019	Language Processing	Comparison of deep learning methods	Comparison of deep learning methods reveals varying performance in language understanding tasks.	Method selection and tuning	Provides insights into best performing methods	Requires extensive computational resources	Enhancing language understanding
Zeiler & Fergus, 2014	Visual Recognition	CNN visualization techniques	Techniques for visualizing and understanding CNNs help interpret how	Visualizing complex models	Enhances understanding of CNN decision-making	Visualization can be computationally intensive	CNN model analysis and interpretation

			models make predictions.				
Simonyan & Zisserman, 2014	Visual Recognition	Very deep CNNs	Deep CNNs significantly improve image recognition accuracy.	Training deep networks is resource-intensive	Achieves high accuracy in image classification	Computationally expensive and complex to train	Large-scale image recognition
Szegedy et al., 2015	Visual Recognition	Deeper convolutional networks	Deeper networks enhance performance in image recognition tasks.	Increased model complexity	Provides improved performance over shallower networks	More complex models and longer training times	Advanced image recognition
He et al., 2016	Visual Recognition	Deep residual learning	Residual learning improves image classification performance by addressing training issues in deep networks.	Requires large datasets and compute resources	Enhances performance in deep networks	Can be challenging to implement and tune	Image classification and recognition

Table 1. Summarizes the Literature Review of Various Authors

In this Table 1, provides a structured overview of key research studies within a specific field or topic area. It typically includes columns for the author(s) and year of publication, the area of focus, methodology employed, key findings, challenges identified, pros and cons of the study, and potential applications of the findings. Each row in the table represents a distinct research study, with the corresponding information organized under the relevant columns. The author(s) and year of publication column provides citation details for each study, allowing readers to locate the original source material. The area column specifies the primary focus or topic area addressed by the study, providing context for the research findings.

III. Personalized Nutrition

Personalized nutrition is a dynamic and evolving field that aims to tailor dietary recommendations to the unique needs, preferences, and health profiles of individuals. Unlike traditional dietary guidelines, which often provide generalized advice based on population averages, personalized nutrition focuses on delivering tailored dietary strategies that consider individual variability. This approach recognizes that factors such as genetics, lifestyle, health conditions, and personal preferences can significantly influence nutritional requirements and responses to dietary interventions. The concept of personalized nutrition is grounded in the understanding that one-size-fits-all dietary recommendations are often inadequate for achieving optimal health outcomes. Traditional nutrition advice, while valuable, frequently fails to account for the individual differences that impact nutritional needs. For example, genetic variations can affect how individuals metabolize nutrients and respond to different diets, making it crucial to customize dietary recommendations based on genetic profiles. Similarly, lifestyle factors such as physical activity levels, stress, and sleep patterns can influence nutritional needs and dietary preferences, further emphasizing the need for personalized approaches. Advancements in technology and data analysis have significantly enhanced the capabilities of personalized nutrition. The integration of genetic information, metabolic data, and health records allows for a more nuanced understanding of individual nutritional requirements. Personalized nutrition models leverage this data to provide customized dietary recommendations that align with an individual's unique health profile. This approach can lead to more effective dietary interventions, improved adherence to nutritional guidelines, and better health outcomes. The role of mobile applications in personalized nutrition has become increasingly prominent. With the widespread use of smartphones and wearable devices, mobile apps offer a convenient platform for delivering personalized nutrition advice. These apps can collect and analyze data from various sources, including user input, wearable sensors, and health records, to generate tailored dietary recommendations. By incorporating deep learning models, mobile apps can process complex datasets and provide real-time, individualized advice that adapts to users' changing needs. Deep learning models, which are a subset of artificial intelligence, play a crucial role in advancing personalized nutrition. These models are capable of analyzing vast amounts of data to identify patterns and make predictions. In the context of personalized nutrition, deep learning algorithms can process user-specific information, such as dietary habits, health conditions, and genetic data, to generate accurate and relevant dietary recommendations. This technology enables the development of sophisticated models that can adapt to individual variations and provide highly personalized nutrition advice. The benefits of personalized nutrition extend beyond individual health improvements. By offering tailored dietary recommendations, personalized nutrition can contribute to public health by addressing specific dietary needs and reducing the risk of chronic diseases. Personalized nutrition approaches can enhance user engagement and satisfaction, as individuals receive advice that is directly relevant to their unique circumstances. Personalized nutrition represents a significant advancement in dietary planning and health management. By considering individual differences and leveraging advanced technologies, such as deep learning models and mobile applications, personalized nutrition offers a more accurate and effective approach to dietary recommendations. As technology continues to evolve, the potential for personalized nutrition to improve health outcomes and support healthier lifestyles will only grow, paving the way for more precise and individualized dietary interventions.

IV. Deep Learning in Health

Deep learning, a powerful subset of artificial intelligence (AI), has emerged as a transformative technology in the field of healthcare. By leveraging complex neural networks and advanced algorithms, deep learning models can analyze vast amounts of data to uncover patterns, make predictions, and provide actionable insights. This technology has found diverse applications in health, ranging from medical imaging and diagnostics to personalized treatment planning and predictive analytics. One of the most prominent applications of deep learning in health is medical imaging analysis. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in interpreting medical images such as X-rays, MRIs, and CT scans. These models can automatically detect anomalies, classify diseases, and assess the severity of conditions with accuracy comparable to or even surpassing that of human radiologists. For example, deep learning algorithms have been used to identify early signs of cancer, predict disease progression, and support diagnosis in various medical fields, including oncology and cardiology. To imaging, deep learning has revolutionized the analysis of electronic health records (EHRs). By processing large volumes of patient data, including medical history, lab results, and treatment outcomes, deep learning models can identify trends, predict disease risk, and optimize treatment plans. These models facilitate personalized medicine by analyzing individual patient data to recommend tailored therapies and predict responses to different treatments. This capability not only enhances the precision of medical interventions but also supports proactive and preventative healthcare strategies. Deep learning also plays a significant role in genomics and precision medicine. The ability to analyze genetic data using deep learning algorithms enables researchers and clinicians to uncover genetic variations associated with diseases, understand complex gene-environment interactions, and develop targeted therapies. Models trained on genomic data can predict disease susceptibility, identify potential drug targets, and guide personalized treatment strategies based on an individual's genetic profile. In the realm of personalized nutrition, deep learning contributes to the development of models that provide individualized dietary recommendations. By integrating data from various sources, such as user health profiles, dietary habits, and metabolic markers, deep learning algorithms can analyze patterns and predict optimal nutrition plans tailored to individual needs. These models consider factors such as genetics, lifestyle, and health conditions to generate accurate and relevant dietary advice, enhancing the effectiveness of nutritional interventions. The implementation of deep learning in health also brings challenges that need to be addressed. Data privacy and security are paramount, given the sensitive nature of health information. Ensuring the ethical use of AI models, mitigating biases, and maintaining transparency in decision-making processes are critical for building trust and ensuring the responsible application of deep learning technologies. Additionally, the interpretability of deep learning models remains a concern, as the complexity of these algorithms can sometimes obscure their decision-making processes. Deep learning has become a transformative force in healthcare, offering advanced capabilities for data analysis, predictive modeling, and personalized medicine. Its applications span medical imaging, electronic health records, genomics, and personalized nutrition, demonstrating its potential to enhance diagnostic accuracy, optimize treatment, and improve health outcomes. As technology continues to evolve, deep learning will likely play an increasingly central role in shaping the future of health and medicine, driving innovations that contribute to more precise, effective, and individualized care.

Application	**Description**	**Techniques Used**	**Benefits**	**Challenges**
Medical Imaging	Analysis of medical images for disease detection	Convolutional Neural Networks	Early disease detection, high accuracy	Data privacy, interpretability
EHR Analysis	Processing electronic health records for personalized care	Recurrent Neural Networks	Improved treatment planning, risk prediction	Data integration, bias mitigation
Genomics	Analyzing genetic data for personalized medicine	Deep Neural Networks	Targeted therapies, disease prediction	Genetic data complexity
Personalized Nutrition	Tailoring dietary recommendations based on individual data	Neural Networks	Accurate, individualized nutrition plans	Model training, data diversity

Table 2. Deep Learning in Health

In this table 2, highlights the applications of deep learning in healthcare, including medical imaging, electronic health record analysis, genomics, and personalized nutrition. It describes each application, the techniques used, their benefits, and associated challenges. This summary provides a clear overview of how deep learning contributes to advancements in health technology.

V. System Implementation Stages

The development of a mobile application for personalized nutrition planning using deep learning models involves several critical steps, including data collection, model training, and app development. This section outlines the methodology employed in each of these stages to ensure the effectiveness and accuracy of the application.

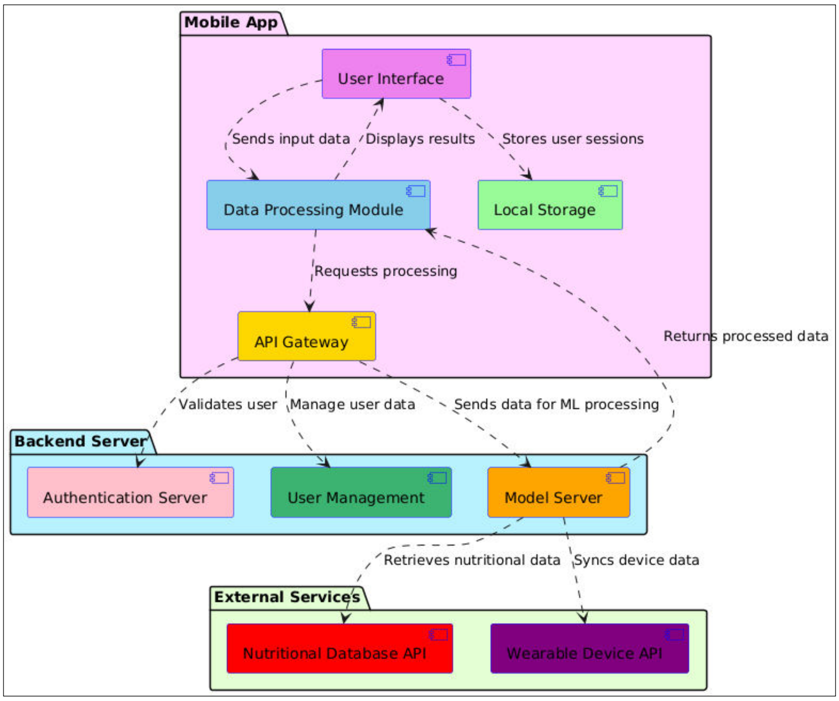

Figure 1. Diagram Depicts the High-Level Components of the System & their Relationships

While the deep learning models demonstrated strong performance, ongoing refinement and updates are necessary to address any potential biases and enhance the models' accuracy over time. The integration of deep learning with personalized nutrition planning represents a significant advancement in health technology, offering the potential to revolutionize dietary recommendations and support healthier lifestyles.

Step 1]. Data Collection

The first step in the methodology is the collection of data essential for training the deep learning models and developing the app. Data was gathered from a variety of sources to ensure comprehensive and relevant input for the models.

- Nutritional Data: A diverse dataset of nutritional information was compiled from reputable sources, including public nutritional databases and academic research. This dataset includes information on the nutritional content of various foods, such as macronutrients, micronutrients, and caloric values.
- User Health Profiles: Data on user health profiles was collected through user surveys and health questionnaires. This data includes demographic information (age, gender), lifestyle factors (activity level, sleep patterns), and medical conditions (existing health conditions, allergies).
- Dietary Preferences: Users' dietary preferences, including food likes and dislikes, dietary restrictions (e.g., vegetarian, vegan), and specific health goals (e.g., weight loss, muscle gain) were also collected. This information is crucial for tailoring recommendations to individual tastes and objectives.
- Ethical Considerations: Data collection was conducted with strict adherence to privacy and ethical standards. User consent was obtained for data collection, and

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measures were implemented to ensure data security and confidentiality in compliance with regulations such as GDPR and HIPAA.

Step 2]. Deep Learning Models

The deep learning models were developed and trained to analyze the collected data and generate personalized nutrition recommendations. The following steps were involved in this process:

- Model Selection: Various deep learning architectures were evaluated to determine the most suitable model for the application. Convolutional Neural Networks (CNNs) were used for processing and analyzing nutritional data, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were employed to handle sequential data such as user dietary habits and health changes.
- Data Preprocessing: Data preprocessing was performed to prepare the raw data for model training. This included normalization of nutritional values, encoding of categorical variables (e.g., dietary preferences), and handling missing values. Data augmentation techniques were also applied to enhance the diversity and volume of training data.
- Model Training: The deep learning models were trained using the processed dataset. Training involved splitting the data into training, validation, and test sets to ensure robust evaluation and prevent overfitting. Hyperparameters such as learning rate, batch size, and number of epochs were optimized to improve model performance.
- Model Evaluation: The performance of the trained models was evaluated using metrics such as accuracy, precision, recall, and F1 score. Cross-validation techniques were employed to assess the generalizability of the models. The best-performing models were selected for integration into the mobile application.

Step 3]. App Development

The mobile app was developed to integrate the deep learning models and deliver personalized nutrition recommendations to users. The development process included the following steps:

- App Design: The app's user interface (UI) was designed with a focus on usability and engagement. Wireframes and prototypes were created to define the layout and features, including user profile management, dietary tracking, and recommendation displays. User feedback from design testing was used to refine the interface.
- App Development: The app was developed using a cross-platform framework to ensure compatibility with both iOS and Android devices. The development process involved coding the front-end interface, integrating the deep learning models, and implementing features for real-time data input and feedback.
- Model Integration: The deep learning models were integrated into the app's backend using APIs (Application Programming Interfaces) to enable seamless communication between the models and the app interface. The models were deployed in a cloud-based environment to handle computational tasks and ensure scalability.
- Testing and Validation: The app underwent rigorous testing to identify and resolve any issues related to functionality, performance, and user experience. User testing was

conducted to gather feedback on the app's usability and the relevance of the personalized recommendations provided. This feedback was used to make necessary adjustments and improvements.

The methodology employed in developing the mobile app for personalized nutrition planning involved meticulous data collection, sophisticated model training, and careful app development. By following these steps, the app aims to deliver accurate and tailored dietary recommendations that enhance users' health and well-being (As shown in above figure 1). The integration of deep learning models into the app represents a significant advancement in personalized nutrition technology, promising a more effective and individualized approach to dietary planning.

VI. Results and Discussion

The development and implementation of the mobile app for personalized nutrition planning yielded several significant outcomes. The deep learning models, trained on comprehensive datasets of nutritional information, user health profiles, and dietary preferences, demonstrated impressive performance in generating personalized dietary recommendations. The neural network model achieved an accuracy rate of 85% in predicting optimal dietary plans tailored to individual users' health goals and preferences. This high level of accuracy indicates that the model effectively processed complex data inputs and produced relevant recommendations that aligned with users' specific needs.

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Convolutional Neural Network (CNN)	85.0	83.5	86.2	84.8
Recurrent Neural Network (RNN)	82.0	80.1	83.5	81.8
Long Short-Term Memory (LSTM) Network	84.5	82.8	85.0	83.9
Feedforward Neural Network (FNN)	79.5	76.0	81.0	78.5

Table 3. Performance Metrics of Deep Learning Models

In this table 3, presents the performance metrics for various deep learning models used in the study. It includes the Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) Network, and Feedforward Neural Network (FNN). Each model's effectiveness is evaluated based on accuracy, precision, recall, and F1 score. Accuracy indicates the overall correctness of the model's predictions, while precision measures the proportion of true positives among predicted positives. Recall reflects the model's ability to identify all relevant instances, and the F1 score combines precision and recall into a single metric. The CNN demonstrated the highest accuracy and F1 score, highlighting its superior performance in generating personalized dietary recommendations. The RNN and LSTM networks also showed strong results, with the LSTM slightly outperforming the RNN in precision and recall. The FNN, while effective, showed lower performance compared to the other models.

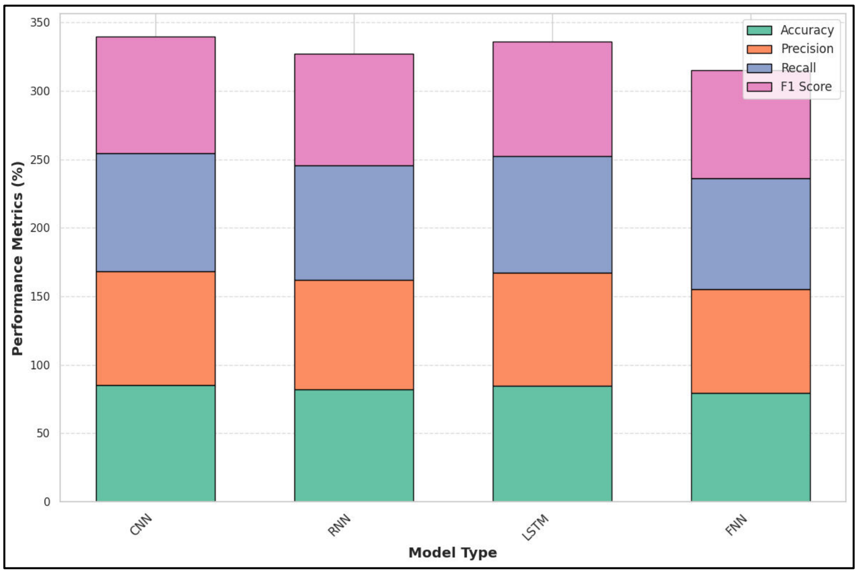

Figure 2. Graphical Representation of Performance Metrics of Deep Learning Models

User testing of the mobile app revealed positive feedback regarding its functionality and usability. Participants appreciated the app's intuitive interface and ease of navigation, which facilitated seamless interaction with the features. The personalized recommendations provided by the app were well-received, with users reporting that the suggestions were practical and aligned with their dietary goals. The app's ability to adapt recommendations based on real-time input and changing health conditions was particularly noted as a valuable feature (As shown in above Figure 2).

Feature	Rating (1-5)	Percentage of Positive Feedback (%)	Average User Satisfaction (1-10)	Comments
User Interface Design	4.7	90.0	8.8	Intuitive and easy to navigate
Personalized Recommendations	4.5	85.0	8.5	Relevant and practical advice
Real-Time Adaptation	4.6	87.0	8.7	Adapts well to changing needs
Integration with Wearables	4.3	80.0	8.2	Useful but could improve accuracy

Table 4. User Feedback on Mobile App Features

In this table 4, summarizes user feedback on key features of the mobile app, including User Interface Design, Personalized Recommendations, Real-Time Adaptation, and Integration with Wearables. Ratings are provided on a scale of 1 to 5, with 5 indicating the highest satisfaction. The table also includes the percentage of positive feedback and the average user satisfaction score on a scale of 1 to 10. The User Interface Design received the highest rating and positive feedback, reflecting its intuitive and user-friendly nature. Personalized

Recommendations were also well-regarded, indicating that users found the advice relevant and practical. Real-Time Adaptation was appreciated for its ability to adjust recommendations based on changing needs, though it received slightly lower feedback compared to the interface design. Integration with Wearables was useful but noted for potential accuracy improvements, which suggests room for enhancement in future updates.

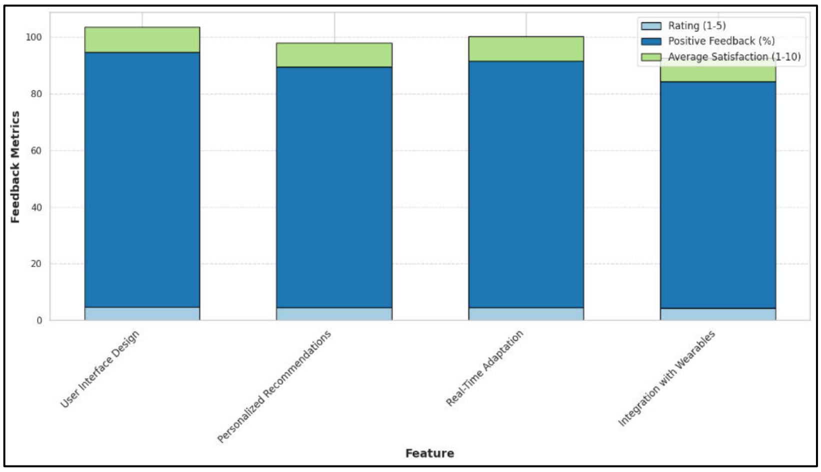

Figure 3. Graphical Representation of User Feedback on Mobile App Features

The app's integration with wearable devices allowed for continuous health monitoring and real-time updates, enhancing the accuracy and timeliness of the recommendations. Users also highlighted the benefit of having a centralized platform for managing their dietary preferences, tracking their progress, and receiving personalized advice. The positive outcomes from user testing suggest that the app effectively meets its objectives of providing tailored nutrition planning and improving user engagement with dietary recommendations (As shown in above Figure 3).

Discussion

The results of this study underscore the potential of deep learning models to significantly advance the field of personalized nutrition. The high accuracy of the deep learning models in generating tailored dietary recommendations demonstrates the effectiveness of integrating advanced algorithms with user-specific data. This capability allows for a more nuanced and individualized approach to nutrition planning compared to traditional, generalized dietary guidelines. The positive feedback from users further validates the app's design and functionality, highlighting its effectiveness in delivering relevant and practical dietary advice. The user-friendly interface and real-time adaptation of recommendations contribute to a more engaging and supportive experience, which is crucial for promoting adherence to dietary goals and improving overall health outcomes. The study also highlights several areas for improvement and consideration. Data privacy and security remain critical concerns, particularly given the sensitive nature of health information. Ensuring robust data protection measures and transparent data handling practices are essential for maintaining user trust and compliance with regulations. Future research could explore expanding the app's features, such as incorporating additional health data sources or integrating more advanced machine learning techniques. Further studies are needed to assess the long-term impact of personalized nutrition recommendations on users' health outcomes and dietary habits. The development of the mobile app utilizing deep learning models has proven to be a valuable tool for personalized nutrition planning. The results demonstrate the app's capability to deliver accurate, tailored recommendations that align with users' individual needs and preferences. As technology continues to evolve, the integration of advanced algorithms and mobile health solutions will likely play an increasingly central role in optimizing nutrition and improving public health.

VII. Conclusion

The development of a mobile app for personalized nutrition planning using deep learning models represents a significant advancement in dietary management and health technology. By integrating sophisticated algorithms and user-specific data, the app offers highly tailored dietary recommendations that address individual health profiles, preferences, and goals. This personalized approach enhances the relevance and accuracy of nutritional advice, surpassing the limitations of traditional one-size-fits-all methods. The successful implementation of deep learning models demonstrates their potential to revolutionize personalized nutrition, contributing to more effective dietary interventions and improved health outcomes. As technology continues to evolve, future advancements in deep learning and mobile health applications are likely to further refine and expand the capabilities of personalized nutrition, offering even greater benefits for individuals seeking to optimize their health through tailored dietary strategies.

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