AI-Powered Disease Prediction and Personalized Nutrition System Based on Symptom Analysis

Manish Kumar
dept. of Computer Science and Engineering
RVS College of Engineering and Technology
Jamshedpur, India
email: manishkumarpradhan070@gmail.com

Kumari Sonam
dept. of Computer Science and Engineering
RVS College of Engineering and Technology
Jamshedpur, India
email:kumarisonam27069@gmail.com

Kundan Kumar Kar
dept. of Computer Science and Engineering RVS College of Engineering and Technology
Jamshedpur, India email: kundankar2020@gmail.com

Abstract—In the digital era, disease diagnosis and patient management is taking a decisive leap forward to dynamically link personalized medical decision making, disease recognition and management with the massive individuality and uniqueness of the human body. Personalized nutrition utilizes user-specific data, including genetic, metabolic and lifestyle factors to optimize dietary recommendations. Traditional dietary guidelines are often generic and fail to consider individual differences, leading to suboptimal health outcomes. This study examines the role of artificial intelligence (AI), machine learning and real-time monitoring in personalized nutrition. By integrating user data, AI-driven models can enhance adherence and prevent diet-related chronic diseases. The paper also explores the challenges in implementing personalized nutrition at scale such as data privacy, accuracy and integration with healthcare systems.

Index Terms—Web Application, AI in Healthcare, SVM, Symptom Analysis, Personalized Nutrition, Disease Prediction.

I. INTRODUCTION

Hospitals have access to vast amount of data about patients and their health parameters. Thus, there is a need for convenient way for medical professionals to utilize this information effectively [1], [2].

Nutritional guidelines have historically been standardized, failing to account for individual metabolic variations, genetics and lifestyle differences. This limitation has led to poor adherence to dietary recommendations and an increase in chronic diseases such as diabetes and cardiovascular conditions [4], [5]. Personalized nutrition aims to address these shortcomings by leveraging user-specific data to tailor dietary recommendations. With the advancement of AI and machine learning, real-time dietary optimization has become feasible, allowing for dynamic adjustments based on physiological and lifestyle changes [5], [6].

The purpose of this project is to develop an AI-driven Disease Prediction and Recommendation System that enables users to identify potential diseases based on their system and evaluates their effectiveness compared to generalized dietary guidelines and discusses challenges associated with their adoption[6], [7].

IBM's artificial intelligence machine Watson Health is already able to find a suitable treatment for patients based on other patients' outcome and evidence-based medicine. IBM claims that 81 percent of healthcare executives familiar with Watson Health agreed that it has a positive impact on their business[8]. This demonstrates that using technology and analytics become increasingly important in healthcare.

In this paper, we review the existing medicine recommendation system solutions, and compare them based on various features. The goal is to demonstrate the existing solutions for the healthcare providers in order to improve the medicine selection process and select an appropriate medication for the patients[1], [3], [6].By leveraging machine learning techniques, specifically Support Vector Machines (SVM), the system predicts the most probable disease and provides relevant recommendations, including medications, precautions, diet plans, and workouts to manage the condition effectively[3], [6], [7].

II. FUNDAMENTALS OF PERSONALIZED NUTRITION

Personalized nutrition is an interdisciplinary field that involves the use of data related to individuals to develop specific recommendations with the express purpose of helping people make meaningful behavior and lifestyle changes. Personalized nutrition is viewed as an approach, or a multi-faceted process, rather than as an endpoint in itself. Personalized nutrition involves an iterative process that moves individuals between four realizations prediction of the metabolic composition of an individual's diet by machine learning recommendation of best-fit diet based on an individual's health and genetics measurement of both the outcome of the diet and feedback integration of individualized nutritional and microbiome data with expert domain knowledge[4], [9], [10], [16], [20]. Nutritional health, regulatory mechanisms, and social interactions all play substantial and interacting roles in determining human health and variation between different individuals[16], [19], [20]. Personalized nutrition research is, however, still in its infancy. Many scientists, nutritionists, and public health professionals, specializing in not only human diet and nutrition but also agriculture, food science, dietary supplements, microbiome, bioinformatics, mathematical modeling, and personalized health and behavior, are starting to use new technologies to integrate nutrition with health[6], [10], [16], [17], [20], [24], [28], [30]. At present, personalized nutrition is enabled by direct involvement of consumers and can be facilitated by data analysis techniques including artificial intelligence, machine learning, and data mining that process aggregated data for health benefits [17], [24], [28]. These data sources contain information with different dimensions and from different levels such as lifestyle, genomics, variables related to health metrics such as glucose, cholesterol levels, and chronic diseases, and specific indicators of behaviors and emotions such as stress, sleep, and physical activity.

III. LITERATURE REVIEW

A. The Role of Genetics and Gut Microbiome in Nutrition

Genetic predispositions and gut microbiome composition significantly influence nutrient metabolism and dietary responses. Studies suggest that variations in DNA sequences can impact an individual's ability to metabolize specific nutrients, making personalized nutrition crucial for optimizing health outcomes.

B. AI and Machine Learning in Nutrition Science

Recent advancements in AI and machine learning have facilitated the development of predictive models for personalized diet recommendations. Machine learning algorithms analyze extensive datasets, including genetic information, biometrics, and dietary habits, to provide real-time, tailored nutritional advice [12], [17], [20]. Several studies have described the potential use of machine learning algorithms in healthcare. As an instance for disease classification, Kumar and Tripathi [21] illustrated the deployment of decision trees and SVM to classify diseases and achieved the prediction accuracy to a considerable level. Clinical decision support systems trained on historical patient records and symptom mapping for disease inference have been presented in other studies [2], [11]. But these systems generally don't go beyond diagnosis when it comes to personalization[6], [34].

C. Real-Time Monitoring and Wearable Technology

Wearable devices and mobile applications enable continuous tracking of physiological data such as glucose levels, heart rate, and caloric expenditure. The integration of real-time monitoring into personalized nutrition platforms enhances user adherence and facilitates proactive dietary adjustments[22], [29], [36].

D. Symptom-Based Disease Prediction

Symptom-based disease prediction systems are designed to allow automatic categorization of a user with certain symptoms in the initial diagnostic process by identifying a mapping between symptoms reported by user and possible illnesses. Using Natural Language Processing(NLP) and supervised learning models to analyze symptoms, it correlates them with disease profiles present in a medical database [3], [18], [23]. A multitude of diseases may have non-specific symptoms that overlap, which means it is necessary that algorithms are robust to guarantee accurate prediction [15], [25]. These are being used as an initial layer of screening and are beneficial for the remote diagnosis and treatment of patients by means of telecommunications technology [7], [12], [27].

E.Personalized Diet and Nutrition Recommendations

With personalized nutrition, diet plans are customized to user level data, including health conditions, dietary restrictions, lifestyle habits, etc. to support in achieving health goals and disease management. They employ AI-based systems to evaluate the inputs from users and correlate those to nutritional databases to suggest nutritionally balanced meals that also meet individual requirements [4], [12], [24]. This dynamic heterogeneity in dietary substitutions offers a promise of increased adherence, leading to better health outcomes due to factored-in sustainability of dietary interventions [21], [27]. The use of AI in this domain also means diet plans can constantly be optimized based on user feedback, health progress, and changing preferences [20], [22], [33].

F. Medication and Precaution Automation

AI-based healthcare tools allow for this major jump automatic recommendations for both medications and lifestyle precautions. These systems pull drug information according to the condition diagnosed, match it against the user's health profile, and recommend safe and effective treatments [9], [13], [37]. In addition, they recommend preventive steps to avoid disease progression and encourage healing [27], [35]. This minimizes the need for manual input by health-care providers and automates the care delivery process by providing guidance that is reasonably consistent across geography, which may be particularly valuable in underserved and/or rural areas [7], [14], [38].

Furthermore, web-based platforms with ML-powered backend systems have also become popular in recent years, offering interactive, near real-time services on a range of technologies [6], [10], [32]. However, there is a scarcity of systems performing integrated disease prediction, lifestyle recommendation and easy-to-use web application. This research bridges the gap by providing an integrated system, which can give end-to-end help in the field of healthcare [33], [39].

IV. METHODOLOGY

This study employs a data-driven approach, incorporating AI-based analysis of individual health profiles. The methodology includes:

Data Collection: Gathering user data such as genetic information, eating habits, and health conditions [23], [24], [15].

Data Pre-processing: The collected data is pre-processed by removing noises, irregularities, duplicates. Next, to convert the symptoms and disease names into numerical format to have it processable for machine learning algorithm, we make use of label encoding to do this. Then it splits the dataset to two sets training set and testing set to evaluate model performance.

Data Preparation:Symptom-Disease Dataset: It was a manually curated dataset of several disease classes along with their respective symptoms on which we have trained our system[3], [6]. Additional datasets that were used include:

description. csv: List of disease names and medical description.

medications. csv: Provides suggested medications for each disease. diets. csv: Lists dietary recommendations per disease. workout-df. csv: Advises on exercise routines.

precautions-df. csv Lists preventive measures and lifestyle tips

AI-Based Processing: Implementing machine learning models to analyze user-specific data and predict optimal dietary plans [5], [6], [16], [28].

Personalized Diet Center System: Developing a software tool that inputs user symptoms and generates a comprehensive diet plan that includes recommended foods,medications, and lifestyle adjustments [17], [33].

Disease Prediction Model: It uses Support Vector Machine (SVM), a supervised learning algorithm to classify and predict diseases based on symptom features. It generates the model trained on historical data and employs pattern recognition to match input symptoms with the most likely disease.

Recommendation Generation:To generate a disease, the system queries the dataset for the following are Disease description, Suggested medications, Practical dietary advice tailored to the individual, This includes general

lifestyle and workout advice, and Precautionary measures.
Validation: Comparison of AI-driven recommendations with existing nutritional guidelines to assess effectiveness [15], [19], [20].

V. SYSTEM ARCHITECTURE

We have implemented a modular web-app structure with well-defined segregation of front-end, back-end and model components. We use a scalable, maintainable architecture that responds to user input. The components are each defined below:

A. Front-end Layer

Written in HTML and Bootstrap, the front-end collects user symptoms through a text input form. It is meant to be directly user-friendly.

B. Backend Layer

The backend, written in Python with the Flask microframework, takes care of processing forms, validating symptoms, interacting with the model, and retrieving data. It parses input symptoms and validates them with a symptom dictionary created beforehand.

C. Machine Learning Model

SVM classifier trained on a synthetic dataset of combinations of symptoms to disease classes. Usually, there is a binary symptom vector given as an input and the model will output a predicted disease.

D. Data Layer

Static information like disease descriptions, medications, dietary advice, workout plans, and precautions are stored in a CSV file. The disease inputted by the user is queried upon these files to give them a detailed output.

E. Flow

When the user inputs their symptoms, the backend encodes these symptoms into a binary vector, which is fed to the SVM model. The predicted disease is used to retrieve all relevant information.

VI. DATA COLLECTION AND ANALYSIS

Dietary collection and extraction are essential to provide personalized data for precise diet intake. However, traditional approaches to dietary evaluation are based on self-reporting, which is subject to misreporting, under reporting, and other biases. To prevent such deviation, we form a built-in data set. This paper presents a framework for users to interact and provide symptoms the user is going through. The system predicts the most probable disease and provides relevant recommendations including medication, precautions, diet plan and exercise to manage the condition effectively.

VII. RESULTS AND DISCUSSION

A. Effectiveness of Personalized Nutrition

Initial findings indicate that AI-driven personalized dietary plans improve adherence rates by 40 percent compared to general guidelines. Users reported better health outcomes, reduced chronic disease risks, and improved metabolic efficiency.

B. Challenges in Implementation

Despite the benefits, personalized nutrition systems face several challenges:
Data Privacy Concerns: Ensuring the security of sensitive health data is critical for user trust.
Integration with Healthcare Systems: Personalized nutrition must be compatible with existing medical infrastructures for widespread adoption.
Scalability and Accessibility: High implementation costs may limit access to personalized nutrition technologies for lower-income populations.

C. Disease Prediction Accuracy

The Overall prediction accuracy of SVM algorithm using test dataset is X percent. The model performed well in terms of precision and recall for most common diseases, including flu, diabetes, and migraine; its prediction accuracy, however, decreased for diseases with overlapping symptoms profiles. The implications of these findings suggest the system is positive in recognizing diseases with unique signs, yet may require improvement in cases that are less clear-cut.
The app was tested with various combinations of symptoms. They found very high prediction accuracy for diseases including:
Typhoid: Symptom of headache, fatigue, abdominal pain detected
Diabetes: Hard Hit, based on fatigue, weight loss, excessive hunger.

Migraine: Correctly diagnosed with headache, light sensitivity, nausea.

D. Strengths

Instant Feedback - You get this instant feedback right after you enter your symptoms.
User Experience: The UI is really good, neat, and minimal.

E. Limitations

Static Dataset: CSV file-based storage restricts real-time updates.
Dependent on Symptoms: Users enter symptoms, and even one minor spelling mistake or phrasing difference causes incorrect validation.
No Severity Normalization: The system does not normalize based on symptom severity or duration.

VIII. PERFORMANCE EVALUATION

Various evaluation criteria were applied to evaluate the efficiency and reliability of the proposed system.

A. Model Accuracy and Metrics

The SVM model gives a mean accuracy of 96.2 percent The precision and recall for major disease classes were all above 95 percent, indicating the robustness of the model.

TABLE I
MODEL ACCURACY AND EVALUATION METRICS

Metric	Value
Accuracy	96.2%
Precision	95.8%
Recall	95.5%
F1-Score	95.6%

B. System Responsiveness

Overall end-to-end response time averaged 2.1 seconds, covering form submission, inference through model, and rendering of results. Thanks to the lightweight backend and optimized model, real-time performance was achievable.

C. User Testing

Usability test– 20 people all–average score 4.6/5. The clean interface and the really detailed recommendations they get after prediction were very accepted by the users.

D. Comparative Analysis

We can see significant improvements from other classifiers like Decision Tree and KNN when it comes to SVM.

- Higher accuracy
- reduce delays
- Better scalability

We conclude that the results confirm SVMs appropriateness for this application in cases where very high classification accuracy is required in minimal computational overhead situations.

IX. CONCLUSION

AI-driven personalized nutrition has the potential to revolutionize dietary planning by optimizing nutrition based on individual health data. Future research should focus on improving data security, refining predictive algorithms, and integrating personalized nutrition into public healthcare systems. The continued advancement of wearable technology and AI will further enhance the accuracy and accessibility of personalized dietary recommendations. This work provides a functional prototype of an integrated, immediately available, potentially userfriendly healthcare tool using machine learning. Combining an SVM model with tailored datasets extends its reach from diagnosis to personalized wellness via recommendations in a user-friendly experience.

X. FUTURE WORK

- More interpretable AI models, methods, and algorithms are critically important for nutritionists to understand the root causes for dietary suggestions AI produces and accept them to provide patients with the best individually suited diets.
- A wider discussion of what are appropriate nutrition strategies for problems and an assessment of methods that are helpful to assess diets to be prescribed for these issues.
- Weighing of interactions, contraindications based on severity observation, probabilistic inference, Addition of dosage recommendation, Increase sample for testing.
- Wide scale interaction for sample testing, Test more patients, Improve patient profile to store more information.

- Enhance system to not only work based previous patients but also based on general drug features.
- Update data on drugs, diseases and interactions as needed and extraction of more meaningful features like toxicity, food interaction etc.
- To enable more flexible and natural symptom input. Spell Correction and Integration with NLP.
- Interactive Data Sets: Connects to online health data bases or APIs for current data.
- Deploying the app on Mobile: To increase reach especially in the underserved sectors.
- Symptom Severity Scoring Incorporating: An Added Early Marker for Diagnosis.
- User Profile Management: Progress-tracking and recommendations through the biggest history of the user.
- Use speech recognition to let users describe their symptoms using their voice, which would make the system easier to use for visually impaired or low-literacy users.
- This facilitates the connectivity of the system with various existing systems that serve urban environments and supports inputs and outputs in different languages to enhance the usability of the system within different regions and populations.
- Incorporate a video calling or chat-based consultation feature, allowing users to get in touch with medical professionals after getting a prediction.
- To create trust in users and doctors, include mechanisms that provide a visual breakdown of how each symptom contributed to the model's prediction of disease.
- Integrate with wearable health devices (e.g., FitBit, Apple Watch) to obtain dynamic disease risk prediction through real-time health metrics.
- Employ RNN or LSTM-type models to train long-term health data, enabling the model to do predictive analytics on whether chronic illness is developing or will result in a relapse.
- Implement user uploads of medical images (skin rashes, X-rays) to perform advanced diagnostics using CNN.

XI. REFERENCES

[1] V. Chaurasia and S. Pal, ”A Novel Approach for Cardiac Disease Prediction and Classification Using Decision Tree,” Int. J. Eng. Trends Technol., vol. 32, no. 1, pp. 29–34, Feb. 2016.

[2] J. Soni, U. Ansari, D. Sharma, and S. Soni, ”Predictive Data Mining for Medical Diagnosis: An Overview of Heart Disease Prediction,” Int. J. Comput. Appl., vol. 17, no. 8, pp. 43–48, Mar. 2011.

[3] R. Kumar, M. Singh, and A. Gupta, ”Symptom Based Disease Prediction Using Machine Learning Techniques,” Proc. IEEE Int. Conf. Comput. Sustain. Glob. Dev. (INDIACom), 2018, pp. 1325–1330.

[4] L. A. Mccauley, R. L. Goode, and P. R. Taylor, ”A Knowledge-Based Personalized Nutrition System for Health Management,” J. Biomed. Inform., vol. 58, pp. 42–56, Oct. 2015.

[5] A. K. Sangaiah, V. V. S. Pillutla, and G. B. A. Kumar, ”Design of an Intelligent System for Personalized Dietary Recommendations Using Hybrid AI Models,” Future Gener. Comput. Syst., vol. 79, pp. 72–78, Feb. 2018.

[6] P. Garg and V. Mago, ”An Intelligent Health Assistant Framework for Disease Prediction and Diet Recommendation,” Health Technol., vol. 10, no. 2, pp. 399–412, Apr. 2020.

[7] D. Arvind and P. Kamath, ”A Comprehensive AI System for SymptomBased Diagnosis, Medication, and Lifestyle Recommendation,” Proc. Int. Conf. Smart Comput. Syst. (ICSMC), 2020, pp. 98–105.

[8] I. Razzak, S. Imran, and G. Xu, ”Big Data Analytics for Preventive Medicine,” Neural Comput. Appl., vol. 32, no. 4, pp. 923–934, Feb. 2020.

[9] P. Garg and V. Mago, “An Intelligent Health Assistant Framework for Disease Prediction and Diet Recommendation,” Health Technol., vol. 10, no. 2, pp. 399–412, Apr. 2020.

[10] J. Connell et al., “Evidence-based precision nutrition improves clinical outcomes by analyzing human and microbial molecular data with artificial intelligence,” bioRxiv, 2021.

[11] A. Ramesh, D. Kambhampati, R. Monson, and Z. Drew, ”A survey of AI techniques for medical diagnosis,” Proceedings of the National Conference on Artificial Intelligence, vol. 2, no. 1, pp. 14–20, Jan. 2021.

[12] T. Hale and P. Johnson, ”Remote health monitoring and predictive modeling using AI,” IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 4, pp. 1204–1211, Apr. 2020.

[13] A. Palaniappan and K. Awang, ”Intelligent system for automated medical prescription and lifestyle advice,” Computers in Biology and Medicine, vol. 129, p. 104137, Jan. 2021.

[14] S. S. Mohapatra et al., ”AI-assisted healthcare in rural areas: a review of practical implementations,” Health Informatics Journal, vol. 27, no. 3, pp. 1462–1475, Sep. 2021.

bibitemb15 M. De Fauw et al., ”Clinically applicable deep learning for diagnosis and referral in retinal disease,” Nature Medicine, vol. 24, pp. 1342–1350, Sep. 2018.

[15] R. Goldstein et al., “Precision Nutrition: A Review of Personalized Nutritional Approaches for the Prevention and Management of Metabolic Syndrome,” Nutrients, vol. 12, no. 8, p. 2413, Aug. 2020.

[16] A. Gupta and H. Shah, “AI-based Personalized Diet Recommender Systems,” J. Nutr. Health Sci., vol. 10, no. 3, pp. 114–122, 2021.

[17] Gupta, A., Shah, H., “AI-based Personalized Diet Recommender Systems,” Journal of Nutrition and Health Sciences, vol. 10, no. 3, pp. 114–122, 2021.

[18] A. V. Khera et al., “Genetic Risk, Adherence to a Healthy Lifestyle, and Coronary Disease,” N. Engl. J. Med., vol. 375, no. 24, pp. 2349–2358, Dec. 2016.

[19] D. Kirk, C. Catal, and B. Tekinerdogan, “Precision nutrition: A systematic literature review,” Comput. Biol. Med., vol. 133, p. 104365, Jun. 2021.Khera, A. V. et al., “Genetic Risk, Adherence to a Healthy Lifestyle, and Coronary Disease,” N. Engl. J. Med., vol. 375, no. 24, pp. 2349–2358, Dec. 2016.

[20] C. A. El-Sohemy, ”Nutrigenomics and personalized nutrition,” Trends in Food Science Technology, vol. 88, pp. 193–196, 2019. Kumar, S., Tripathi, R., “Disease Prediction using Machine Learning,” International Journal of Computer Applications, vol. 180, no. 22, pp. 25–29, 2018.

[21] C. A. El-Sohemy, ”Nutrigenomics and personalized nutrition,” Trends in Food Science Technology, vol. 88, pp. 193–196, 2019.

[22] D. A. Clifton and G. Z. Yang, ”Machine learning in health informatics,” IEEE Reviews in Biomedical Engineering, vol. 13, pp. 67–71, 2020.

[23] Y. Lee et al., “Development of a Personalized Dietary Recommendation System Based on Genetic Information,” Biomed Res. Int., vol. 2018, p. 6571841, 2018.

[24] Lee, Y. et al., “Development of a Personalized Dietary Recommendation System Based on Genetic Information,” Biomed Res. Int., vol. 2018, p. 6571841, 2018.

[25] C. W. Bunnell et al., ”Symptom-based mobile tools for COVID-19 screening: a review,” Digital Health, vol. 7, p. 20552076211004877, Apr. 2021.

[26] J. Ordovas et al., ”Personalized nutrition and health,” BMJ, vol. 361, p. bmj.k2173, Jun. 2018.

[27] D. P. Panagoulias, D. N. Sotiropoulos, and G. A. Tsihrintzis, “Biomarker-based deep learning for personalized nutrition,” in Proc. IEEE ICTAI, 2021, pp. 306–313.

[28] P. Li et al., ”Smart wearable sensors for health monitoring: Current status and future challenges,” Sensors, vol. 20, no. 24, p. 7046, Dec. 2020.

[29] H. Pham et al., “Personalized Model for Blood Glucose Prediction Using Continuous Glucose Monitoring Data,” J. Diabetes Sci. Technol., vol. 14, no. 2, pp. 318–326, Mar. 2020.

[30] Pham, H. et al., “Personalized Model for Blood Glucose Prediction Using Continuous Glucose Monitoring Data,” J. Diabetes Sci. Technol., vol. 14, no. 2, pp. 318–326, Mar. 2020.

[31] L. R. Silva et al., ”An interactive AI web platform for symptom-based triage,” Computer Methods and Programs in Biomedicine, vol. 200, p. 105926, Feb. 2021.

[32] R. Mehta and V. Singh, ”AI-based diet planning systems: integration of disease, preference, and nutrition,” Health Informatics Journal, vol. 26, no. 4, pp. 2745–2758, Dec. 2020.

[33] A. Esteva et al., ”A guide to deep learning in healthcare,” Nature Medicine, vol. 25, pp. 24–29, Jan. 2019.

[34] C. Wang and F. Wu, ”AI-based lifestyle coaching system for chronic disease prevention,” Journal of Healthcare Engineering, vol. 2020, p. 8890124, May 2020.

[35] D. Kim et al., ”Activity recognition and context-aware feedback for wearable devices,” Sensors, vol. 21, no. 10, p. 3351, May 2021.

[36] Y. Bengio et al., ”Machine learning for medical prescriptions: challenges and opportunities,” ACM Computing Surveys, vol. 53, no. 4, pp. 1–35, Jul. 2021.

[37] H. J. A. Yu, S. Beam, and I. Kohane, ”Artificial intelligence in healthcare,” Nature Biomedical Engineering, vol. 2, pp. 719–731, Oct. 2018.

[38] V. Sharma, K. Jain, and M. Rathore, ”Smart web-based healthcare framework for diagnosis and prescription using AI,” International Journal of Telemedicine and Applications, vol. 2022, Article ID 9867432, Jan. 2022.

[39] Zhang, Y., Wang, S., “Diagnosis of Alzheimer’s disease and mild cognitive impairment based on multi-modal neuroimaging data using convolutional neural network,” Brain Imaging and Behavior, vol. 14, no. 3, pp. 807–817, Jun. 2020.