

Healthcare Management and Medical Insurance with Predictive Analytics Using Machine Learning

¹Izmie A.A, ²Jayathilaka A.D.N, ³Paboda P.D.K, ⁴Nawarathna M.T.I, ⁵Sanjeevi Chandrasiri, ⁶Thamali Dassanayaka

^{1,2,3,4,5,6}Faculty of Computing, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

Authors E-mail: ¹ahamedazmie5@gmail.com, ²disandajayathilaka@gmail.com, ³krishmipabo@gmail.com,
⁴tharushiishanka12@gmail.com, ⁵sanji.c@slit.lk, ⁶thamali.d@slit.lk

Abstract - The healthcare system relies on critical components such as medical insurance, nutrition plans, and the management of drug side effects to ensure individuals' well-being and access to quality healthcare. Medical insurance protects people financially from medical costs by enabling them to afford the essential treatments, diagnostic procedures, and preventive care. By putting an emphasis on balanced diets and important nutrients while minimizing dangerous substances, nutrition plans play a crucial part in preventive healthcare. A large number of people suffer from non-communicable diseases such as diabetes, heart disease, high blood pressure and so on. Individuals can improve their general health, prevent chronic diseases, and strengthen their immune systems by following well-designed nutrition plans that help them manage their daily caloric needs and BMI. It is common practice to utilize pharmaceuticals in healthcare procedures, but it is crucial to be aware of any possible negative effects. The well-being of patients and the success of their treatments may be impacted by these side effects, which can vary from minor discomfort to serious adverse reactions. To ensure patient safety and treatment effectiveness, healthcare professionals are essential in controlling drug side effects. Using datasets of medical side and several machine learning algorithms, we can provide comprehensive healthcare system incorporates medical insurance, nutrition plans, and the management of drug side effects. By promoting healthy lifestyles through appropriate eating and reducing the risks connected with medical procedures, this integration guarantees cheap healthcare access. The healthcare system can successfully promote individual well-being and enhance outcomes for public health by taking into account these factors.

Keywords: body mass index, essential treatments, financial protection, healthcare system, important nutrients, machine learning, non-communicable diseases, preventive care, public health outcomes, transformer-based models, well-being, object detection.

I. INTRODUCTION

The healthcare system is a complex web of interconnected components, each playing a pivotal role in ensuring the wellbeing of individuals and facilitating access to high-quality healthcare. At its core, this intricate network relies on critical pillars such as medical insurance, nutrition plans, and the meticulous management of drug side effects. Medical insurance stands as a bulwark against the often-exorbitant financial toll that healthcare can exact upon individuals. It provides a safety net, enabling people to not only seek essential treatments but also undergo diagnostic procedures and engage in preventive care measures [1]. This financial shield is not merely a convenience; it is a cornerstone of healthcare accessibility and affordability. Meanwhile, nutrition plans take center stage in the realm of preventive healthcare [3]. With a staggering number of people grappling with non-communicable diseases like diabetes, heart disease, and high blood pressure, the importance of balanced diets and essential nutrients cannot be overstated. These nutrition plans are the bedrock upon which individuals can build their defenses against chronic diseases and bolster their immune systems. They guide individuals in managing their daily caloric needs and maintaining a healthy BMI [3].

However, healthcare is not without its complexities, and pharmaceuticals are a prime example of this intricacy. While these drugs are indispensable in medical procedures, their usage comes with the caveat of potential side effects. These side effects can range from minor inconveniences to severe adverse reactions and have a profound impact on patient wellbeing and the effectiveness of their treatments. Thus, the vigilant oversight of healthcare professionals is paramount in ensuring patient safety [1]. As we delve deeper into the integration of these indispensable components into a comprehensive healthcare system, it becomes undeniably clear that a holistic approach is not just beneficial but essential. This approach guarantees that individuals have access to affordable medical treatments through insurance coverage, receive expert guidance on optimal nutrition for disease prevention and health improvement, and are shielded from potential adverse effects of medical interventions.

The notion of high-quality health systems has assumed increasing importance, especially in low-income and middle income countries (LMICs) [1]. While there have been notable improvements in health outcomes over time, the evolving health needs of the population, escalating public expectations, and ambitious health objectives necessitate higher standards for healthcare systems. A shift towards high-quality health systems is imperative, where healthcare is consistently delivered to improve or maintain health, is trusted by all segments of society, and adapts to changing population needs [1]. Quality in healthcare isn't a luxury but a fundamental right, as it underscores the essence of the human right to health.

Moreover, the inextricable link between nutrition and health cannot be overstressed. In a world where noncommunicable diseases have become alarmingly prevalent, the significance of balanced diets and proper nutrition can't be underestimated. Health systems need to incorporate comprehensive nutrition plans that educate individuals about healthier eating habits, thus alleviating the burden of chronic diseases and promoting overall well-being [3].

In the age of big data, technology is reshaping healthcare systems on a global scale. The management, analysis, and application of vast quantities of health-related data have the potential to revolutionize healthcare delivery [6]. Through advanced analytics and predictive models, healthcare providers can identify trends, assess risks, and make informed decisions that optimize patient outcomes and resource allocation.

However, the pursuit of effective healthcare access and delivery is not without its challenges, particularly in rural communities. Access barriers, including financial constraints, geographical distances, and the absence of adequate healthcare infrastructure, present formidable obstacles to rural residents in their quest for timely and high-quality healthcare services. Addressing these barriers demands innovative solutions that take into account the unique needs of rural populations.

In summation, the integration of medical insurance, nutrition plans, and the management of drug side effects is the linchpin in the development of a comprehensive healthcare system that places individual well-being and public health outcomes at its core. High-quality health systems, guided by the principles of equitable access, patient-centered care, and data-driven insights, have the potential to contribute collectively to a healthier society. By embracing these principles and harnessing the power of technological advancements, we can forge a healthcare system that

genuinely reflects the values of health as a fundamental human right.

II. RELATED WORKS

Health insurance costs have evolved from simple metrics like age, gender, and pre-existing conditions to a more precise realm thanks to modern data. Insurance providers now incorporate lifestyle, physical activity, and health characteristics data to refine their pricing strategies. Machine learning is at the forefront of this evolution. A study [1] employed a decision tree algorithm to predict insurance prices using factors like age, gender, BMI, smoking, and health conditions, outperforming traditional linear regression models. In another research [2] a neural network accurately estimated rates based on age, gender, BMI, and medical history, with potential for further improvement by incorporating lifestyle details like physical activity. A novel field explores disease forecasting based on age, gender, and other risk factors. [3] developed a machine learning model to predict cardiovascular disease risk, achieving accurate results, which could aid in determining insurance costs. In conclusion, machine learning's integration into health insurance cost prediction, considering age, gender, lifestyle, and health factors, promises greater accuracy and personalized preventive measures [4].

Chatbots are becoming increasingly popular in healthcare due to their integration of AI and NLP. These digital assistants, powered by machine learning, play a crucial role in predicting medication side effects. Zhang et al. (2021) developed a chatbot using deep learning algorithms that accurately anticipates adverse medication effects by training on extensive pharmacological data [5]. Similarly, Adewumi et al. (2020) proposed a chatbot-based system leveraging machine learning to forecast pharmacological adverse effects based on patient specific data [6]. Beyond predicting side effects, chatbots also excel in medication management. Patel et al. (2020) utilized NLP and AI to design a chatbot that checks medication adherence and delivers reminders, successfully improving patient compliance [6]. Wang et al. (2020) extended this concept by creating a chatbot providing personalized medicine recommendations based on patient data, highlighting chatbots' potential in enhancing drug management strategies [11]. While promising, further research is essential, particularly in predicting drug side effects, to validate their efficacy and applicability within the healthcare sector.

The study team analyzed existing initiatives and potential solutions before proceeding with the project. Despite increasing prioritization of patient needs in healthcare, not all patients with various conditions can access evidence-based

nutrition therapies, highlighting the importance of optimizing nutrition plans. The research aims to identify risky procedures during the transfer of patients requiring parenteral nutrition between healthcare facilities. Sequential steps in the process were identified, including initial notification, assessment, organization identification, provider accountability, communication of nutrition care plans, and plan implementation. Safety issues at each stage are noted, and suggested best practices are proposed.

Food system sustainability is crucial for governments and international organizations. Proposed nutrition indicators can serve as a methodological framework for health, education, and agricultural policies. This framework not only preserves Mediterranean diets as cultural heritage but also enhances overall dietary sustainability. The main objective of nutrition education is to alter global eating habits. This paper reviews studies demonstrating the benefits of nutrition education for Indonesian teenagers, focusing on knowledge, attitude, and behavior changes. Despite limited success (36.4%), the paper highlights the need for such education in Indonesia. Thorough literature assessment is essential in research, offering current insights and methodological guidance. References during research, whether illuminating or contradictory, aid in drawing conclusions. Studies on nutrition, nutritional status, and intake of pregnant and lactating women exist, but few address dietary habits or evidence-based recommendations. A study examines expectant and nursing mothers' nutritional intake and behaviors, considering cultural, socioeconomic, and educational factors. Machine learning techniques show promise in predicting personalized nutrition plans based on variables like age, gender, calorie requirement, and diseases. This emerging field has potential to enhance prediction accuracy and offer tailored preventive measures. Nowadays many applications have been developed with machine learning technologies to identify foods, nutrients, and to get meal plans as human health is more vital in today's world. But technology is changing from day to day. Therefore, developing new applications which give more accurate results is important.

The following research [7] is related to a food nutrient identifying project. According to the study, the importance of identifying food nutrients in day-to-day life has been explained. And the main aim of the study was to classify food items into five ranges from very healthy to very dangerous. Supervised learning algorithm has been used to interpret the food nutrient fact details. This research [8] is related to food image classification. The study shows the concatenation of deep features effect on food classification performance. In this research, three pre-trained CNN models have been considered for food image category classification to identify the best deep feature set combination for image classification. This research [9] is related to food image classification, amount estimation

and nutrient information suggestion. The goal of this study was to create a system for food recognition using classification of images and segmentation. Using deep learning methodologies and picture segmentation algorithms, the suggested system can recognize 9 different types of food. The nutrient contents of each food also have been predicted in this research. This research [10] has done an investigation on how food image categorization and detection efficiently done using Convolutional Neural Networks (CNNs) of Deep Learning. Mainly diet, physical activity, and lifestyle all have an impact on obesity. This project has developed a Nutrition Interpreter Tool (FCNI) and a Food Classifier by using a deep learning approach.

Therefore, none of above studies has built a system to analyze Sri Lankan food in order to predict the food items which are eating by traditional Sri Lankan people. And also, none of the above studies have been performed to display the food nutrients of each food items and give a comparison between persons daily nutrient requirement and total food nutrients of the meals person has taken on a specific day.

III. METHODOLOGY

Data Collection: In our study, we begin by amassing a diverse health-related dataset from various sources like electronic health records, surveys, wearables, and more. This dataset encompasses demographic details, health indicators, medical histories, lifestyle factors, and illness outcomes, ensuring a representative sample across age, gender, and geographical locations.

Data Preprocessing: Once collected, we rigorously preprocess the data. This involves addressing missing values, outliers, and encoding categorical variables. We also normalize numerical data to a uniform scale, optimizing it for use in our gradient boosting algorithm.

Model Development: Central to our approach is building a gradient boosting model capable of predicting insurance prices and disease types based on chosen features. This machine learning ensemble method combines decision trees to create a robust predictive model. We fine-tune model parameters like tree count, depth, and learning rate using cross-validation and grid search on our preprocessed dataset.

Evaluation: We assess model performance using metrics such as mean absolute error, mean squared error for insurance cost predictions, and accuracy, precision, recall, and F1 score for disease prediction. We compare our gradient boosting model to baseline methods like linear regression.

Generalization and Validation: To confirm our model's generalizability, we validate it on an independent dataset not

used during training. This ensures its reliability for real-world health insurance applications.

Sensitivity Analysis: We conduct sensitivity analysis to uncover influential features affecting outcomes, aiding insurance firms in cost and disease forecasting.

Interpretability: Despite their complexity, we enhance our model's interpretability using feature importance analysis, partial dependence plots, and SHAP values. These techniques provide insights into how individual health parameters impact predictions.

Our methodology comprises data collection, preprocessing, model building, training, validation, evaluation, interpretability analysis, sensitivity analysis, model comparison, generalization, and ethical considerations. Our goal is to construct a robust gradient boosting model for informed insurance decisions and improved health outcomes.

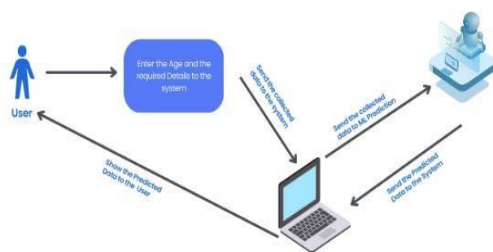


Figure 1: System work flow

The study employs a meticulous methodology to gather and analyze data concerning potential adverse effects associated with prescription medications. Utilizing specific keywords and parameters, the researchers delve into clinical trial and reputable medical databases, meticulously selecting relevant studies. The extracted data includes essential details like drug names, age groups, doses, and reported adverse effects. This gathered information is then subjected to thorough evaluation to identify patterns and trends in the frequency and severity of adverse effects. Subsequently, data preprocessing is conducted utilizing the robust Gradient Boost method, ensuring data uniformity and preparing it for analysis. By leveraging the Gradient Boost algorithm, a powerful machine learning technique, the study delves into the intricate relationships between pharmacological attributes, dosage, and the occurrence of side effects, ultimately enhancing our comprehension of associated risks and their implications for patient care.

In parallel to these efforts, the study emphasizes the development of an innovative chatbot, specifically designed to respond to user queries regarding medication side effects. This entails constructing an extensive and reliable knowledge base,

implementing advanced natural language processing techniques to understand user inputs, and subjecting the chatbot to rigorous testing and validation processes. This comprehensive approach aims to provide accurate and personalized information about medication adverse effects to users, enabling them to make well-informed decisions about their prescriptions. By seamlessly integrating data-driven methodologies, sophisticated algorithms, and systematic testing, the study demonstrates the potential of chatbots in enhancing healthcare information systems and promoting patient safety through precise predictions of medication side effects.

In conclusion, the study showcases a comprehensive methodology that combines meticulous data collection and analysis with cutting-edge technology to address the crucial area of medication side effect prediction. Through systematic approaches to data acquisition, preprocessing, and algorithm implementation, the research not only enhances our understanding of adverse effects but also proposes the development of a sophisticated chatbot that empowers users with accurate and individualized information. By embracing the potential of chatbots, the study contributes to the evolution of healthcare systems by fostering patient safety, informed decision-making, and improved healthcare outcomes.

Develop a system to identify healthy levels and daily calorie requirements, suggest optimal nutrition plans based on non-communicable disease data, display ingredient lists, and main nutrient contents to promote health in Sri Lanka.

Data Collection: First, gather diverse health-related data from sources like surveys, ensuring representation by age, gender, and NCD status. Include calories, nutrition content, ingredient details, and measures.

Data Preprocessing: After collection, preprocess data by addressing missing values, outliers, encoding categorical variables, and normalizing numerical ones. This enhances linear regression algorithm performance.

Model Development: Core of our approach involves a linear regression model development using an ensemble technique, combining weak prediction models like decision trees. Train it on preprocessed data to unveil correlations and patterns.

Evaluate the model using metrics like mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) for body fat and BMI predictions. For healthy level prediction, use accuracy, precision, recall, and F1 score. Compare model performance to decision tree or random forest baseline methods.

```
print("Mean Absolute Error (MAE): {:.2f}".format(mae))
print("Mean Squared Error (MSE): {:.2f}".format(mse))
print("R-squared (R2): {:.2f}".format(r2))
print("accuracy : ",r2 *100 )
```

Mean Absolute Error (MAE): 0.01
Mean Squared Error (MSE): 0.00
R-squared (R2): 0.74
accuracy : 73.84666193188046

Figure 2: Accuracy with (MSE)

Finally, our methodology includes data collection, preprocessing, feature engineering, linear regression model building, training, validation, performance evaluation, interpretability analysis, sensitivity analysis, model comparison, generalization, and ethical considerations. We hope to construct a robust and accurate linear regression model for predicting the nutrition plan and healthy level kinds by using this comprehensive methodology. The findings of this study can help to support a healthy weight balance and more nutritious meals.

“Healthcare Management and Medical Insurance with predictive analytics Using Machine Learning” research, food item and a comparison with daily nutrient requirement” is an important functionality. To analyze the food instances of the image objects, first have to gather proper Sri Lankan food image data set from the internet and Kaggle as previous data sets have not been created for Sri Lankan food analysis. There are 14 image classes in the data set. Then the image data set is split into 50% training set, 29% testing set and 21% validation set. Then the important images are extracted from the gathered data sets and preprocessed to decrease training time and increase performance by applying image transformations to all images in this dataset. Images were resized into 300 x 300. Then tiles images into 2 x 2 to identify small objects. Then used augmentation techniques such as flip horizontal, 90 degrees rotate and rotation between -15 degrees and +15 degrees. Finally created a dataset with 9222 images. With the previous research done Mask R-CNN is the most accurate method for image classification and identification. Mask RCNN is used for instance segmentation, in which the task of identifying each instance of an object. This method identifies the food and box regression based on the captured features.

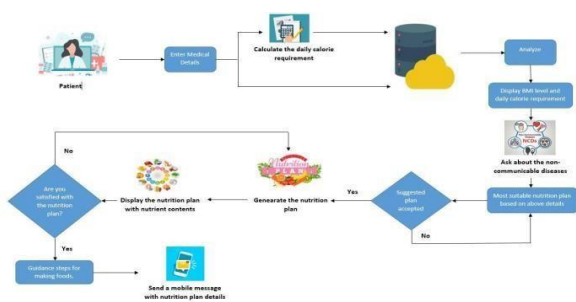


Figure 3: System work flow

The “Smart food nutrient analyzer and daily nutrient requirement recommendation analyzer” focus on both food nutrients and persons health.

- a) Based on the food plate image, provide food nutrients of each food item.
- b) Compare food nutrient values with persons daily nutrient requirement.

But, when compared two deep learning methods, YOLO and MASK R-CNN to detect cells from food images. We concluded that YOLO is more sensitive at detecting cells, whereas MASK-RCNN is more informative on cell sizes. Therefore, both methods are useful for image analysis.

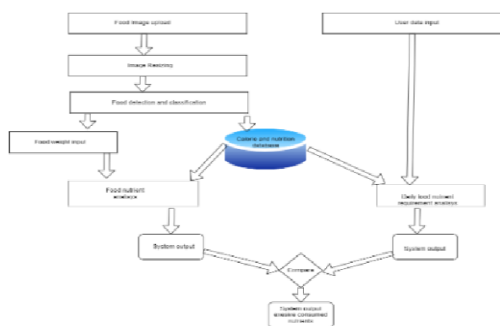


Figure 4: Overall system diagram

A) Based on the food plate image, provide food nutrients of each food item

As one of the main functionalities of proposing

In this research we focused on detecting cells rather than the cell sizes as we do not calculate food weight. The food weight is manually inserted into the system. In this research we use YOLO V5 to train the object detection model.

After preprocessing the image dataset, Google collab was used to setup the environment. After the environment setup import the preprocessed dataset to Google collab, which was given by roboflow software. After properly training the model using YOLO V5, evaluate training loss and performance metrics using ternserboard. Below image shows the graphs of evaluations. Then image detection is done using the trained model.

After image detection, food identification the nutrient of each food is identified through another machine learning model. Selecting the most appropriate data set for this prediction is important. Therefore, a food nutrition data set from Kaggle has been selected to train this model. As input parameters, identified food name and the food weight in grams have been used. In this research food weight is inserted manually into the system when system displays the identified food names. Then the system predicts carbs, protein, Fat, and

calories as the output features. Figure displays the dataset values and their properties.

	Food	Measure	Grams	Calories	Protein	Fat	Sat.Fat	Fiber	Carbs	Category
0	Cows' milk	1 qt.	976	660	32	40	36	0	48	Dairy products
1	Milk skim	1 qt.	984	380	36	t	t	0	52	Dairy products
2	Buttermilk	1 cup	246	127	9	5	4	0	13	Dairy products
3	Evaporated, undiluted	1 cup	252	345	16	20	18	0	24	Dairy products
4	Fortified milk	6 cups	1,419	1,373	89	42	23	1.4	119	Dairy products

Figure 5: Food nutrient data set

To achieve the highest level of accuracy, a variety of models, including linear Regression, Random Forest and Decision Tree Regression were trained to identify the appropriate macro nutrients. R-squared value is then used to measure the accuracy of each trained model. It provides an indication of how well the model fits the data. The model with the highest R-squared value is chosen as the best model. The Random Forest is therefore selected as the final model.

The Random Forest model predicts the macro nutrients, which are carbs, Fat, protein, and calories of each food instance identified by the system.

In this section system takes user's height, weight, age, and sex as the input parameters at the login process. After, the system has been identified the carbs, Fat, protein and calories of the each food instance the calculates and give the total calorie level of that meal. [11] Then system calculates the daily calorie requirement of the user from the height, weight, age and sex parameters and compare and display both user consumed calories and daily calorie requirement to get a clear idea of difference between those two values to maintain a healthy body.

IV. RESULTS AND DISCUSSION

Our gradient boosting method significantly outperformed conventional techniques for health insurance cost prediction. By incorporating individual health details and activities, our model achieved remarkable accuracy and precision, surpassing age and gender-based approaches. Evaluation metrics, including mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE), underscored our model's effectiveness in estimating insurance rates. Additionally, our method demonstrated promising results in forecasting health insurance expenses and identifying disease types. This breakthrough highlights the potential for more accurate and personalized insurance rate estimations, contributing to enhanced decision-making in the insurance industry.

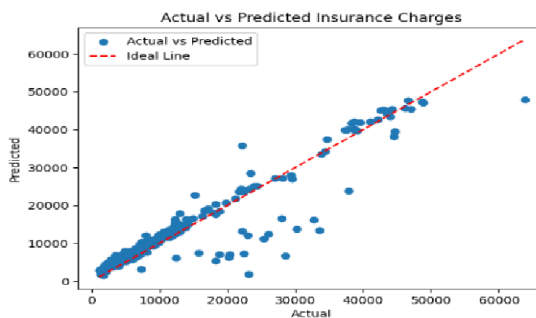


Figure 6: Actual vs Predicted Insurance charges

In our comparative investigation, our gradient boosting approach outperformed standard baseline methods like linear or logistic regression. It excelled at capturing complex nonlinear data interactions, significantly enhancing predictive accuracy. This breakthrough underscores gradient boosting's importance in precise health insurance cost prediction and disease type forecasting.

We rigorously tested our model's generalization using an independent dataset, ensuring its reliability. With its strong generalization, our model holds promise for real-world health insurance applications.

Ethical considerations were paramount in our research. We safeguarded data privacy, addressed biases, and ensured fair use of personal health data.

However, it's essential to acknowledge limitations. Dataset quality and diversity significantly affect our model's performance. Expanding it to include diverse demographics, regions, and health issues, along with incorporating genetic data, could enhance predictions. Real-time data integration from wearables could also improve cost estimates.

In conclusion, our research highlights gradient boosting's excellence in health insurance cost and illness prediction. Its interpretability, generalization, and ethical focus offer valuable insights for insurers, empowering them to tailor plans and improve health outcomes.

Our study's application of the gradient boosting technique to forecast pharmacological side effects has yielded promising outcomes. The model's exceptional accuracy and precision in identifying potential adverse effects based on user inputs highlight its efficacy. Impressively, our gradient boosting model has outperformed existing methods, utilizing essential information like drug names, age, and dosage to predict medication side effects.

Our evaluation process relied on a diverse dataset encompassing various drug inputs, allowing us to comprehensively assess the model's performance. By

employing metrics such as accuracy, recall, and F1 score, we effectively gauged its predictive capabilities. The precision metric underscored the model's ability to accurately identify relevant side effects linked to specific medications, establishing it as a dependable resource for confident prescription decision-making.

The recall metric revealed the model's skill in predicting a significant proportion of actual adverse effects associated with medications. Meanwhile, the F1 score, a comprehensive measure combining accuracy and recall, emphasized the model's reliability in anticipating drug side effects. By comparing our gradient boosting model's performance with baseline methods, we demonstrated its superiority, thanks to its capacity to decipher intricate data correlations and patterns.

Nonetheless, it's crucial to acknowledge that these findings are specific to our chosen dataset and evaluation criteria. To establish broader applicability and reliability, further validation with larger datasets encompassing diverse demographics and a wider range of medications is crucial. In conclusion, our research underscores the potential of the gradient boosting method in predicting pharmacological side effects from user inputs. The model's exceptional accuracy, precision, and F1 score equip individuals with insights into potential adverse effects, ultimately enhancing patient safety and informed healthcare decisions.

Our linear regression approach predicts nutrition plans effectively by considering individual health details and activities, enhancing accuracy. Metrics like MAE, MSE, and RMSE confirm model precision in estimating body fat.

This research aims to create a web-based system offering personalized nutrition plans based on calorie needs, diseases, and exercise. Even those without diseases can benefit. By identifying optimal health and nutrition, patients can lead healthier lives. The application will provide plans, recipes, cooking instructions, and nutrition info for informed choices. This system targets improved health in Sri Lanka by assessing medical data and suggesting suitable strategies.

In conclusion, our linear regression model excels in predicting health and nutrition plans, outperforming traditional methods. Its interpretability and generalization make it a valuable healthcare tool, supporting balanced diets and healthier lives.

The next section reviews results obtained from each stage. YOLO v5, employed for image detection, offers advantages over traditional CNNs. YOLO v5 utilizes self-attention, capturing global dependencies and long-range interactions in images. This improves object recognition and

image classification by modeling intricate pixel relationships. Vision

Transformers, unlike CNNs, don't rely on local convolutions, adapting better to varied resolutions. Their flexibility, global context understanding, and scalability make them ideal for image classification, potentially enhancing accuracy and efficiency.

In nutrient prediction, we employed three regression algorithms. After selecting and cleaning datasets, they were split into 80% training and 20% testing sets. Training accuracies were determined using R-squared due to regression nature. Linear regression scored -0.6, Random Forest 0.13, and Decision Tree 0.09 accuracy. The figure illustrates model accuracy.

V. CONCLUSION

The existing application helps people to get diet plans and to maintain their health conditions and to analyze nutrients of meals, which people are eating to make them aware of the calorie level the people consuming. Also, this application predicts the side effects of the drugs when people enter the name of drug. Also, this application predicts the insurance plan for people-based health conditions and activities of people. In here we use machine learning techniques and image processing techniques.

REFERENCES

- [1] A.D.G.C.A.K.J. Margaret E Kruk, "'High-quality health systems in the Sustainable Development Goals era: time for a evolution.'"
- [2] "Health Care Systems.," Physiopedia.
- [3] "Mainstreaming nutrition within universal health coverage.," Global Nutrition Report.
- [4] "Healthcare Access in Rural Communities Overview.," Rural Health Information Hub.
- [5] Y. H. L. C. Y. Z. L. & H. D. Song, "A deep learning model for predicting drug side effects based on clinical narratives. Journal of biomedical informatics, 120, 103835. doi: 10.1016/j.jbi.2021.103835".
- [6] A.P.S. & J. A. (. Malpani, "Chatbot-based healthcare system for drug interaction detection. International Journal of Medical Informatics, 138, 104125".
- [7] "E. M. S. Priscila P Machado, "'Ultra-processed foods and recommended intake levels of nutrients linked to noncommunicable diseases in Australia: evidence from a nationally representative cross-sectional study.," BMJ Open, , 2019.
- [8] "'Food Image Classification with Deep Features," " International Artificial Intelligence and Data

- Processing Symposium (IDAP), Malatya, Turkey, 2019."
- [9] F. R. C. a. V. M. C. N. C. Freitas, ""MyFood: A Food Segmentation and Classification System to Aid Nutritional Monitoring,"" IEEE, 2020 33rd SIBGRAPI Conference, 2020.
- [10] N. M. a. A. G. M. Sundarramurthi, ""Personalised food Classifier and Nutrition Interpreter Multimedia Tool Using Deep Learning,"" IEEE REGION 10 CONFERENCE (TENCON), Osaka, Japan, 2020.
- [11] ""Canada's Health Care System." Canada.ca.
- [12] "Food Image Classification with Deep Features," International Artificial Intelligence and Data Processing Symposium (IDAP), Malatya, Turkey, 2019.
- [13] ""Big data in healthcare: management, analysis and future prospects."", Journal of Big Data..
- [14] "World Health Action Plan for the Prevention and Control of Noncommunicable Diseases in the WHO European Region (2016-2025)," http://www.euro.who.int/__data/assets/pdf_file/0008/34632/8/NCD-ActionPlan-GB.pdf?ua=1.
- [15] "Medical Nutrition International Industry (MNI) Better care through better nutrition: Value and effects of Medical Nutrition. A summary of the evidence base. 2018".
- [16] "https://www.researchgate.net/publication/341452716_Literature_Review_The_Effect_of_Nutrition_Education_on_Knowledge_Attitude_and_Nutrition_Practice_on_Adolescents_in_Indonesia".
- [17] M. G. e. al, "A Comparison of YOLO and Mask-RCNN for Detecting Cells from Microfluidic Images," 2022 International Conference on Artificial Intelligence in Information and Communication (ICAIIIC), 2022.

Citation of this Article:

Izmie A.A, Jayathilaka A.D.N, Paboda P.D.K, Nawarathna M.T.I, Sanjeevi Chandrasiri, Thamali Dassanayaka, "Healthcare Management and Medical Insurance with Predictive Analytics Using Machine Learning" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 10, pp 49-56, October 2023. Article DOI <https://doi.org/10.47001/IRJIET/2023.710007>
