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Investigation on Food Detection and Nutrients Science using Modern Artificial Intelligence and Machine Learning for Health Care Management

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ABSTRACT - The goal of Artificial Intelligence (AI) is to imitate intellectual processes, knowledge-based management and learning abilities. AI has several uses in the medical research, clinical settings and health care oriented systems. The field of diseases prediction, biomedical, health care application and food sciences has seen an extension of AI-based applications coupled with Machine Learning (ML) in recent decades. An AI with ML have a lot of impending in the areas of risk assessment, medical diagnostics, identification of critical diseases, food safety, healthcare, support for treatment and analyzing the root cause for the disease. The paper's goal is to look at the utilization of AI in the domain of nutritional based science research and the health care system. It illustrates how computer-based decision-making processes works and might assist to improve health and medical treatment. A cutting-edge system built on machine learning that accurately classifies food photos and calculates food qualities automatically. Although machine learning and advanced statistics form the basis of AI, the subject of neural networks is currently undergoing revolutionary developments. In order to improve categorization accuracy, experiments were conducted using a range of food categories, with each category containing many numbers of images.

Keywords: Health Care, Food Safety, Nutrients Science, AI, ML, CNN

I INTRODUCTION

To address this growing concern in food safety and health management, researchers are exploring various approaches to monitor food calorie intake. One such approach is to use technology, such as computer vision algorithms and deep learning models, to classify food images and estimate their calorie content. In this research, experimentation is made with different food categories, each having huge number of images, to train our model. The goal was to develop an accurate and efficient system for food calorie estimation that could be used by individuals to monitor their daily food intake and maintain a healthy diet. The results of this study showed promising outcomes, demonstrating the potential of this technology to support individuals in managing their food calorie intake and promoting healthy eating habits. Nevertheless, more research is needed to refine and improve the accuracy and generalizability of these models across different food types and cultural backgrounds.

The link between obesity and various serious and chronic health conditions has been established, leading the American Medical Association to recognize obesity as a disorder requiring medical attention in 2013. To effectively manage weight and maintain a healthy diet, it is crucial to monitor daily food intake. The traditional method of recording and analyzing food intake over the past 24 hours can be effective, but often leads to patients forgetting or avoiding the use of these programs due to discomfort. Different data's were analyzed for the literature review suggesting various ideas related to health and food management. This paper focuses on AI with nutritional based epidemiology, biomedical oriented nutrients research, and clinical nutrients research. The ML based algorithms were extensively employed in research on the micro-biodata and the influence of nutrients.

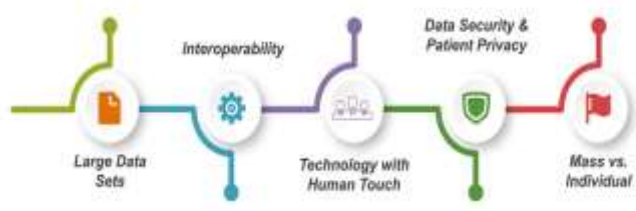

Figure 1: AI in Health Management System

In recent years, interdisciplinary scientific study, political based discussion, and social activism revolved the growing interest using of AI in medicine and healthcare. The figure 1 represents the flow graph for health management system. To maximize the usage of biomedical AI, this information aims towards the benefits of AI in the healthcare and medical based industry, which helps to identify the major risks that are associated with its application. It helps the developers and the physicians' involvement in putting AI-based mediated healthcare that are guaranteed to the security and reverent treatment of patients receiving it.

II SYSTEM DESIGN AND IMPLEMENTATION

The aim is to shed light on the various elements, processes and tools used in the implementation of the system and how they contributed to its desired outcomes and functions. The methodology that is used in this study is a multidisciplinary approach that is based on a comprehensive review and analysis of literature from diverse sources, including biomedical based research, computer science, biomedical ethics, social sciences, law, industry and government oriented reporting. It examines various technical challenges and solutions, clinical research, findings, government recommendations, and best practices that are used of AI in medicine and healthcare. The paper begins by highlighting the potential of AI in addressing pressing problems in medicine, such as an ageing population, increasing chronic diseases, shortage of medical professionals, incompetence of health based systems, health disparities and the lack of sustainability.

This report delves deeper into the specific contributions made and yet to be made by AI in various medical specialties including the cardiology, radiology, digital based pathology, medical risk, emergency based medicine, surgery, prediction of disease, home care application, and mental health in the context of clinical practice. The report highlights the potential benefits of AI for biomedical research, such as clinical trials, drug development, and personalized treatment. Additionally, the report discusses the potential impact of AI on global health and public health. However, the report also acknowledges the potential dangers of AI in medicine and highlights the need for responsible development and distribution of AI systems.

The illustration provided in the report depicts the application of AI in healthcare: In the healthcare domain, these human factors include healthcare professionals, clinicians, and the patients. Even when the robust and accurate, AI technologies are reliant on how humans consume them in the practice and data they provide are employed. Inappropriate use of AI tools can clue to imprecise medical valuation and decision-making, which ultimately detriment the patient.

Figure 2: Role of AI in Healthcare

Lack of training in medical AI between the lack of considerate, healthcare oriented professionals, and the illiteracy between the patients, and the growth of eagerly available in mobile and online AI results without enough explanation and information are all potential factors that contribute to the misuse of AI. The absence of clearness in the creation, assessment, and the utilization of AI based tools is a major concern aimed at the technology. Transparency is crucial at two levels: traceability of AI development and usage ability of actual AI decisions.

Figure 3. Application of AI in Healthcare

Figure 2 and 3 highlights the role of AI with its application in healthcare. The absence of transparency can lead to a lack of understanding and trust in AI predictions and decisions, difficulty in individually evaluating and reproducing of AI algorithms, problems in recognizing the bases of AI based errors and determining responsibility and limited adoption of AI based tools in the clinical exercise and real-world based settings. These risks and their impact on AI implementation are described in detail in the report.

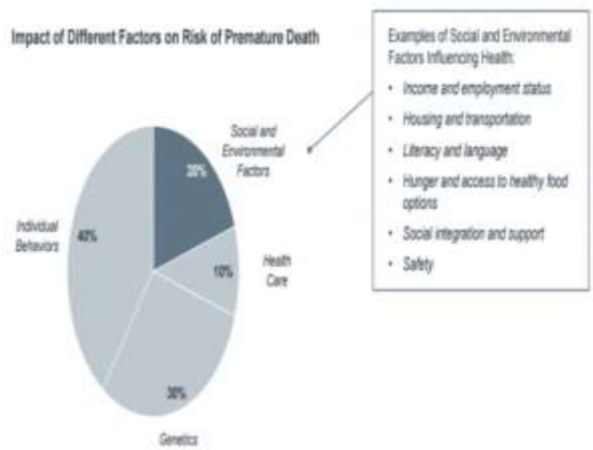

Figure 4: Risk of Premature Death

As a result, it's important to establish clear definitions of accountability and responsibility in the medical AI process. This includes specifying who is responsible for the development, deployment, and use of the AI model and who is responsible for monitoring its performance and ensuring that it is aligned with ethical and safety standards. In order to promote transparency and accountability, it is crucial to establish clear guidelines and regulations for the use of medical AI. This will not only ensure that healthcare professionals are held responsible for their actions, but it will also provide a clear framework for the use and development of AI models. The lack of clear guidelines and regulations can lead to confusion and the potential for harm, which must be avoided at all costs. By establishing clear guidelines and regulations, the medical AI industry can build trust with the public and healthcare professionals, which is essential for the continued growth and development of this field. Different algorithms and approaches to AI in health and health care system are shown below.

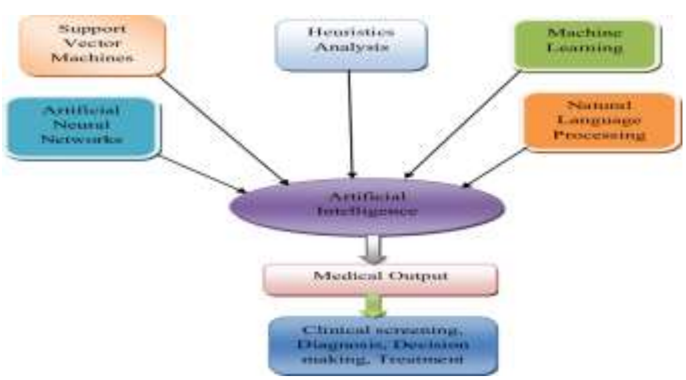

Figure 5: System Flow Diagram

A new structured method of risk management with assessment approach is necessary for the implementation of AI in healthcare and medicine, addressing the technological, clinical, and ethical challenges that arise from its use. Figure 5 explains the system flow of AI in health care. The potential harm and likelihood of harm can be used to categorize and regulate AI concerns through a risk assessment framework. In 2021, the European Commission published a proposal for an AI regulation aimed at harmonizing AI laws across Europe. AI technologies that conflict with EU values are considered illegal and fall into the highest category. Medical AI technologies fall under the intermediate category, considered high-risk AI, and are only approved if they comply with strict guidelines for effective risk based management, like providing human based oversight and conducting the post-market based monitoring.

The proposed AI regulation by the European Commission is a broad approach to regulate AI across all sectors, including healthcare. However, this approach fails to take into account the specific risks and unique characteristics associated with AI in the medical industry. The current regulations, MDR and IVDR, were established when AI was still in its early stages and do not address issues such as identifying algorithmic biases. While the European Commission's proposal attempts to harmonize AI regulation across Europe, it also retains some of the limitations of MDR and IVDR, such as the lack of mechanisms to address the continually evolving nature of medical AI technologies.

The potential for AI in healthcare and medicine is vast, but so are the potential dangers. To mitigate these risks, a structured approach to risk assessment and management is crucial. Some countries had developed the ALTAI assessment checklist, which covers seven elements of reliable AI, including technical healthiness and safety, the human agency and inaccuracy, the privacy and the data governance, and more. However, this approach is not specific to AI in healthcare. A network of research projects and international experts have come together to create consensus recommendations for reliable AI in medicine, known as FUTURE-AI, which includes six categories and a self-assessment checklist to assist with creating trustworthy and ethical AI solutions for the medical industry. It is crucial to detect and manage the potential dangers posed by medical AI through comprehensive evaluations. Despite the importance of evaluating clinical safety, effectiveness, fairness, transparency, and privacy, most research in this field has primarily focused on model accuracy and tool robustness in laboratory settings. To ensure reliable and ethical AI solutions in healthcare, a more comprehensive and multi-faceted evaluation approach is needed. To meet the unique risks and needs of healthcare, it is recommended to enhance AI regulatory frameworks and codes of conduct through domain-specific risk assessment, as different medical specialties may have varying clinical and ethical concerns.

The future of medical AI technology must undergo standardized and comprehensive risk assessment that takes into consideration not just model robustness and accuracy but also clinical acceptance, fairness, safety, transparency, and traceability. The current regulatory framework must be strengthened to identify and address the multifaceted risks and limitations of AI in healthcare. Multi-stakeholder engagement is crucial for the success of medical AI systems in the real world. AI developers should collaborate with clinicians, patients, social scientists, healthcare managers, and regulators to ensure that the AI tools are designed and implemented in a way that meets the diverse needs and circumstances of the real world. A new approach is needed to promote inclusive, multi-stakeholder participation in medical AI development. Medical AI solutions should be created based on a collaborative and inclusive approach that involves end-users, AI developers, and relevant specialists like biomedical ethicists. This will allow for the creation of AI algorithms that better represent the needs and cultures of healthcare workers and identify potential hazards early on. Additionally, traceability and transparency can be improved by establishing methods such as AI passports that provide standardized information about the AI technology and its lifecycle. The AI passport should include information on models, data, evaluation, usage, and maintenance to provide consistent traceability across nations and healthcare organizations.

AI based systems or autonomous based systems are extensively used in nearly all aspect of technology. This allows for the efficient optimization of issues, computerization of the food industry, and transformation of food industry products. The industry may evaluate and ensure that the best circumstances, like crop monitoring, seed selection, watering, and the temperature monitoring, that can be improved by employing a computerized system, which will result in the perfection of the food sector goods. These are not the only applications of AI. Robotics and intelligent drones are only two examples of intelligent devices that can significantly and critically contribute to reducing the cost of packaging. Food security management and food quality management are the two major categories into which the significant responsibilities of AI in the food industries may be divided.

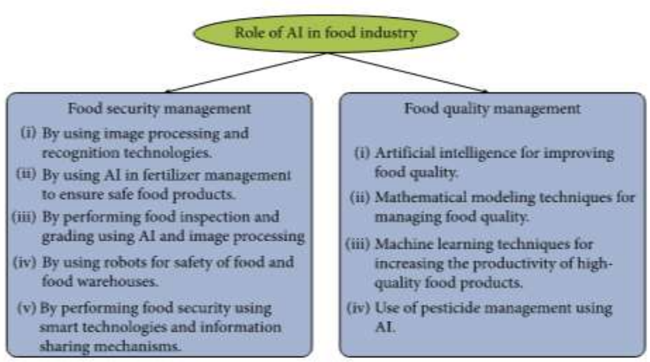

Figure 6: AI in Food Industry

Figure 6 narrates the role and functionalities of AI in food industry. Finally, to improve accountability in medical AI and food AI, the roles and responsibilities of the AI developers, healthcare providers, patients, and regulatory bodies must be clearly defined and effectively monitored.

Figure 7: AI in Food Processing Industry

This can be achieved by incorporating methods of continuous performance assessment, such as monitoring data, performance, and audits. Additionally, creating incentives for all stakeholders to act in a responsible and ethical manner will also contribute to the establishment of a fair and reliable medical AI ecosystem. In order to enhance the validity and efficacy of medical AI technologies, it is important to promote further research on the robustness of its clinical, ethical, and technical aspects. It should focus on areas such as explainability, interpretability, bias mitigation, privacy, and security in AI. Additionally, the development of methods for adaptation to ensure generalizability of AI tools across different populations, therapeutic settings, and geographical locations must also be explored. Furthermore, incorporating uncertainty estimation into medical AI solutions will provide valuable indicators of confidence for clinicians in AI predictions.

III PRE-TRAINED MODEL SELECTION

In this proposed methodology, process is divided it into three separate sections to ensure clear and organized implementation. The first section concentrates on utilizing transfer learning-based Convolutional Neural Network (CNN) models, the second section deals with retrieving text from various sources, and the final section focuses on training the text data.

A. Pre-Trained Convolutional Neural Network Model

In the realm of machine learning, pre-trained network models are employed to overcome the problem of the system becoming trapped in a local solution during the training phase. These models are capable of performing machine learning quickly in response to various inputs. In this method, transfer learning-based CNN model is used to extract attributes from food items in our produced dataset. This approach allows for faster and more accurate recognition and extraction of food attributes.

B. Dataset Preparing and Per-processing Phase

It employs a transfer learning-based Convolutional Neural Network (CNN) to classify food images into their respective categories and extract relevant attributes. Our dataset consists of thousands of food images and approximately 1.8 GB of text data collected from Common Crawl and Scrapy sources. To increase the efficiency of the training data, data augmentation techniques is applied, such as using a spatial transform network to transform the images. The goal of this approach is to enhance the model's ability to classify and extract attributes from food images accurately.

C. Architectural Overview

The system was designed with server-side architecture with the goal of improving the accuracy of pre-trained models. This allows developers and architects to utilize the system by creating their own web-based and Android-based applications on the client side. The three modules in Figure 8 are responsible for processing food names to generate relevant information for training a classification model using CNN. The first module, Text Data Retrieval, retrieves text data from websites by extracting URLs and using Google search, based on the categorized food name provided by a pre-trained model.

The retrieved data is then processed by removing HTML tags and stop words using Python tools and further preprocessed through lemmatization and stemming. The processed text data is used as input for the next module, Text Data Training, which trains the data using the word2vec method. The final module trains the classification model using CNN, which can be used to categorize food items accurately. Figure 8 gives the description of proposed system.

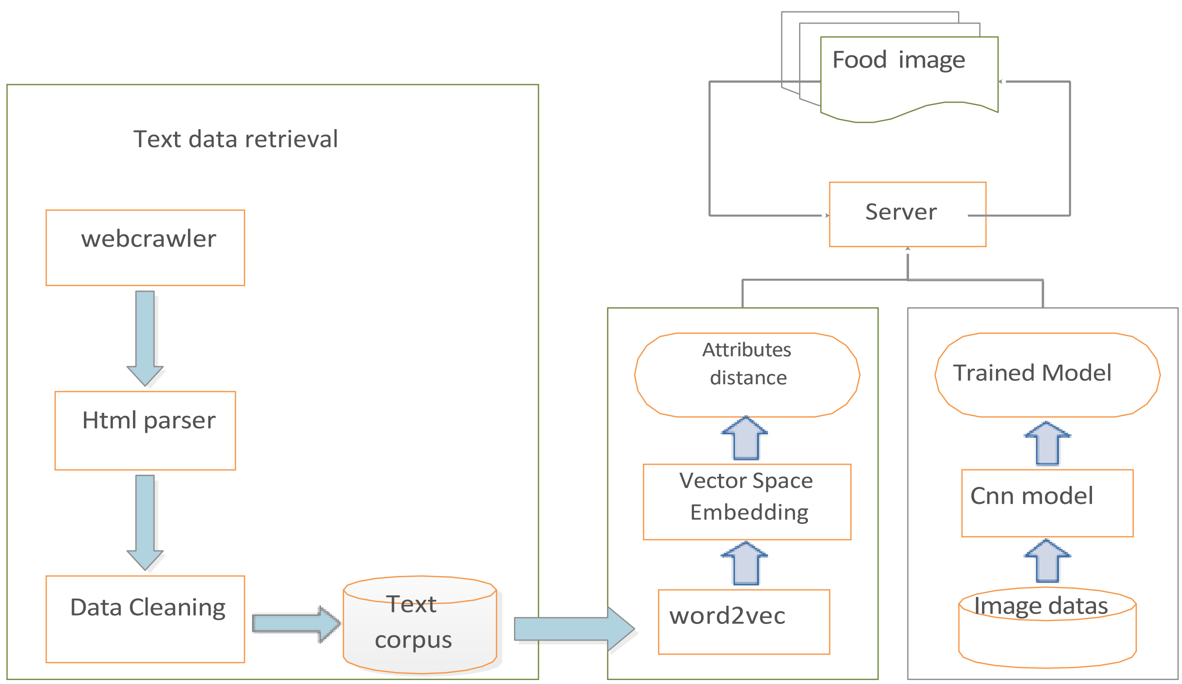

Figure 8: Block Diagram of Proposed System

D. Textual Data Model Training

The vector representation of words is calculated using the Word2Vec machine learning technique, which is a more advanced algorithm than clustering and is used to replace it as a two-layer neural network. The training of text data utilizes three methods, including Word2Vec, Continuous Bag of Words, and Skip Gram, to produce effective results. These methods have been implemented to enhance the accuracy and performance of the text data training process. The attributes and ingredients are initially classified and divided into groups based on their relevance, to facilitate the extraction process. The distance between the attributes and ingredients and their respective classes is determined by fixing the food class and iterating all of the attributes and ingredients against it. The trained Word2Vec model is used to extract traits and components from the text data. The corpus of text data is then trained using Word2Vec to obtain vector space embedding for semantic similarity. These models can predict the features and attributes of an image based on the input provided. The classification and division of attributes and ingredients play a crucial role in determining the distance between them and their associated classes.

The proposed system starts with the creation of picture and textual data, which leads to the final stage of categorization and identification of ingredients and attributes. The gathered food photos are preprocessed using data augmentation to increase the diversity of the data. The pre-trained CNN model is then trained and fine-tuned to improve its accuracy. The categorization phase begins with user input and uses the output from the previous stage as input for the attribute estimation model. The attribute estimation model is created by first preprocessing the raw text data and using the Word2Vec program to generate vector embeddings based on the distances between the words. These embeddings serve as the basis for the attribute estimation model to predict relevant ingredients or attributes.

IV RESULTS AND EVALUATION

Before our system can classify images in the dataset, training is necessary. The training process takes place on a Linux-based operating system, with Python 2.7 and 3.6, and the Anaconda Python distribution being installed. The Anaconda environment is set up by using specific commands, followed by the installation of essential packages like Theano, Pygpu, and Keras within the environment. The model is implemented using Python and the Keras package with Tensor Flow. Experiments with several CNN models were conducted to extract features from around 50,000 photos, with the Inception model having the best accuracy of 91.73%. The final two convolutional blocks were trained by deleting the final fully connected layer from the Inception model and adding previously trained weights to the new model. To combat over fitting, techniques such as data augmentation, batch normalization, dataset enhancement, and regularization were used, along with multi-crop evaluation during prediction.

Table 1: Comparison of models in terms of Single and Multiple Crops

Model		Top-1	Top-2	Top-3	Top-5
Inceptionv3	Single corpus	79.8%	87.9%	91.6%	95%
	Multiple corpus	89.12%	-	-	98.31%
Inceptionv4	Single corpus	83.8%	89.8%	92.4%	94.7%
	Multiple corpus	91.73%	-	-	98.56%
V4-101	single corpus	78.3%	85.4%	88.2%	91.2%
	Multiple corpus	-	-	-	-

After conducting thorough research and testing, the Inception-v3 and Inception-v4 Convolutional Neural Network (CNN) models were selected for the proposed problem domain as they consistently showed better performance compared to other models. These models were fine-tuned using both custom created datasets and Food-101 datasets to further improve their accuracy and compare their performance. The fine-tuning process involves adjusting the parameters of a pre-trained model to better fit the specific problem domain, in this case, food classification. The results of this process showed that the Inception-v3 and Inception-v4 models have a high level of accuracy and are suitable for use in our proposed system.

Figure 9 a. Top-1 Most accurate of inception-v4 model

Figure 9 b. Top-1Least accurate class

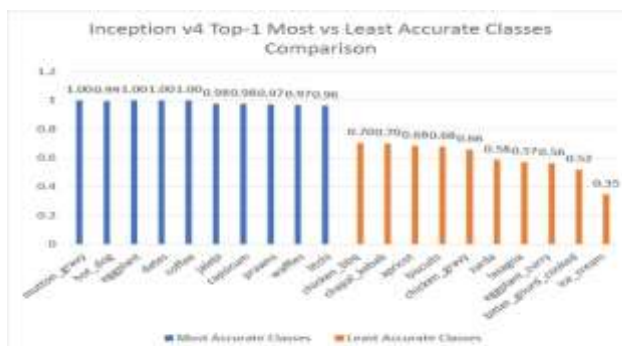

Figure 10: Comparison of top-1 Most Vs Least accurate classes

Figure 11.a Top-1 Accuracy comparison

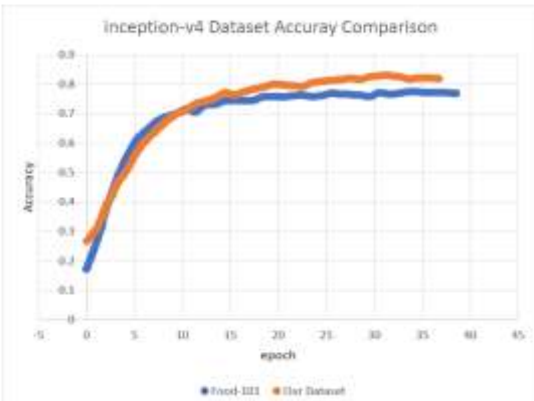

Figure 11.b Inception-v4 model based performance

V. FUTURE WORK

This section explains the drawbacks current and improvements as future work.

A. Recognition and Detection of various food

With existing techniques, it is challenging to identify and analyse mixed physical representations. They do not include cooked, liquid, or composite foods like sandwiches and salads. In a subsequent study, the issue of processing a mixed food image and a physical image that resembles cooking by combining image segmentation technique solves the issue of the image having oblique edges or each other causing the recognition detection to fail.

B. Enhancement of Systems and Datasets

The outcomes of the detection are significantly influenced by data sets and features. Existing data sets are insufficient and only include a small number of characteristics, such as diverse backgrounds, camera angles, lighting conditions, etc. Better review methodologies [13] should be utilized in future studies to examine different kinds of data sets. The system and application are also architecturally improved, and to process the image, a database for calculating values, food labels, and other parameters is integrated with a quicker lookup method.

C. Calories Awareness and Nutrition aware

Understanding calorie calculations and their significance is crucial. The literature [13] addresses the field's issues in light of a brief fast food questionnaire, while the literature [14] employs gaming techniques to gather more food and calorie information. By adding additional calories to evaluate nutritional attributes and combining with deep learning techniques, the basic understanding of calorie computations among users can be improved.

VI CONCLUSION

At this time, obesity is a major issue for people. People are curious about measuring their weight and maintaining a healthy diet. This methodology presents a fresh way to give us knowledge about the kind of food we eat and its properties. Using a range of AI and ML methodologies, food analysis, awareness, risk, health, and safety-based variables are investigated. The algorithm will tell us of the features of the dish once it has correctly classified the user-provided food photograph. A dataset that includes a typical Food-101 meal and food from the subcontinent has been used by our system. In order to recognize food items, modification is done with the Inception V-3 and V-4 models. The proposed method determines the attributes of the food using the attribute estimation model. The results are enhanced via data augmentation, multi-cropping, and other related techniques. The categorization and attribute extraction accuracy of our recommended method is very high at 89%. Further potential improvements to the system's accuracy and usability can be enhanced in future.

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