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FOOD IMAGE ANALYSIS AND DIETARY ASSESSMENT VIA DEEP MODEL USING HYBRID CNN WITH RNN

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ABSTRACT: India has a wide variety of cuisines with great diversity in all food groups included in the diet by the different communities and in the different geographic regions of the country. The dietary diversity of Indians needs adequate attention in order to understand the association between diet patterns and the risk and increasing prevalence of NCDs. Acknowledging the pivotal role of nutrition, this paper introduces "DeepFood," a robust deep learning system designed to provide valuable insights into portion estimation and calorie counting, fostering a comprehensive understanding of individuals' dietary choices. Deep Food’s efficacy has been thoroughly evaluated through extensive experimentation on widely-recognized food image datasets like Fruits-360 with featuring bounding annotations. DeepFood consistently exhibited exceptional accuracy and efficiency in food item recognition. The system's reliability and precision underscore its potential as a cutting-edge solution for addressing the challenges of modern nutritional awareness, empowering users to make informed dietary decisions. DeepFood stands as a promising advancement in leveraging deep learning methodologies to enhance the understanding and management of nutrition in our dynamic and health-conscious society.
Keywords: DeepFood, Food Image Analysis, food item recognition, Hybrid CNN with RNN, modern nutritional awareness

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1. INTRODUCTION

The functions of nutrients and nutrition in maintaining human health and prevention of disease can be fulfilled only when foods that supply the nutrients are ingested. The nutritional value of a diet depends on the choice and quality of ingredients, cooking methods applied food combinations within a recipe or in a meal and hygiene practices followed at all stages of food preparation and service. However, one of the significant influences on the acceptance and ingestion of food is the sensory appeal of food as determined by its taste, texture, aroma, flavour, appearance, and colour. The overall quality of a meal or diet may be a sum of all or some of these parameters. There is a need to determine a framework for producing relevant diet quality indicators . The construction of diet quality scores frequently depends on the features selected by the investigators, in line with their research objectives. A diet quality index comprises components such as the number of items or elements, their respective cut-off values to define an optimal diet, and scoring criteria. The nutrition transition has changed traditional Indian diets, which have shifted away from cereals towards higher consumption of fruits, vegetables, oils and livestock products. This has been attributed to changes in food prices, expenditure patterns and demographic characteristics, lifestyle changes in diet diversification, particularly shifts in food choices with an emphasis on foods with the potential for aggravating the risk of NCDs.

The unique benefits of the colour pigments will be enhanced if at least three pigments are consumed together. This it would increase the diversity in the diet. The authors listed 'unique' and 'very unique' health effects that they observed in the systematic reviews, meta-analysis and RCTs they had included. The very unique effects were attributed to a single colour pigment giving the health benefit, and unique health benefit would be derived when three or more pigments are taken together. They ranked the benefits based on the GRADE system which is Grading of Recommendations, Assessment, Development and Evaluations, a systematic, transparent tool used for grading the robustness of research and quality of evidence which is best suited for the outcome also used for presenting summaries. It grades evidence on four levels- very low meaning that the true effect is significantly different from the estimated effect, low indicating the true effect is probably different from the estimated, medium/moderate suggesting that the true effect is probably close to the estimated effect and high showing that the true effect is similar to the estimated effect.

The recommendations given in the review were that the dietary guidelines must emphasise the consumption of a variety of colours while recommending the intake of fruits and vegetables. There is a need to develop reliable and valid tools to measure the quantity of various coloured fruits and vegetables consumed which will focus on colour-associated food variety. Agricultural research on increasing the concentration of these bioactive pigments in fruits and vegetables; also reintroduce fruit and vegetable varieties discontinued for streamlining agriculture production needs to be considered. Lifestyle factors and the type of diet consumed are the modifiable factors which can prevent and protect the body against chronic illnesses. The right choice of foods and dietary diversity can ensure nutrient adequacy, regulate and reduce oxidative stress and inflammation. Conscious food choices, promoting home-cooked meals, reducing the intake of ultra-processed foods, and increasing the intake of fruits and vegetables that are seasonal and locally grown can help. Increasing awareness about the right food choices, nutrient content of foods and nutrition via simple, easy-to-understand and useful tools which are not restricted only to the nutritionist or wellness consultant but have the potential to involve the patient or the client to become self-reliant, to self-monitor the disease condition and actively participate in making dietary choices rather than been given dietary choices, should be considered.

2. REVIEW OF LITERATURE

P.B. Deshmukh, et.al [1], india has emerged as a country with a triple burdenof malnutrition in spite of its vast and diverse cuisines and traditional dietary patternsthat were healthy. Severe acute malnutrition (SAM) and moderate acute malnutrition(MAM) are prevalent among 7.7% and 19.5% of children under five years of age, respectively (NFHS – V, 2019-2021). This has not changed much from NFHS IV (2019-2021), which found that 7.7% of children under five suffered from SAM and 19.3% from MAM. The phenomenon of "thin-fat" with a dual burden of micronutrient deficiencies is common across all age groups. The prevalence of anaemia has increased from 58.6% (NFHS - IV) to 67.1% (NFHS-V) in children fewer than five years. At the same time, the prevalence of obesity, especiallyabdominal obesity, is increasing among children and adults and becoming the third burden of malnutrition.

N. A. A. Rauf, et.al [2], identified three aspects of diet quality: intake of nutrients appropriate for age, sex, physical activity and disease status, dietary diversity, and food choices of unhealthy and healthy foods as well as food groups consumed in limited or excess proportions. Thus, the three aspects focussed on sufficiency, diversity and adequacy/excess of nutrients in the diet in order to assess its quality. From the perspective of prevention of NCDs, pro-inflammatory diets withproportionately higher intakes of fats, especially saturated and trans-fat, sugar, salt, and ultra-processed foods, as compared to fresh fruits, vegetables, whole grains and minimally to moderately processed foods, can be regarded as poor-quality diets. Good-quality diets will have a higher proportion of a variety of foods taken from allfood groups, which are home-made minimally or moderately processed. For ensuringthe adequacy of micro and macro-nutrient intakes, dietary diversity (DD) is an essential aspect.

T. Ege et.al [3], a detailed review by Rule on using DD as an effective tool for assessing diet quality stated that DD is a crucial element of high-quality diets. Dietary diversity has been defined as "the number of different foods or food groups consumed over a reference period". Several tools and scales for measuring dietary diversity are in use; however, the method still lacks standardisation. The Dietary Diversity Score (DDS) is one of the simplest methods and has been used in numerousstudies to find the association between the intake of food and micronutrients.

V. B. Kasyap, et.al [4], the index does not count the number of serving consumed by an individual as per dietary guidelines. Rather, it is the count of either the numberof foods or food groups consumed. When only single foods are counted, it is calleda Food Variety Score (FVS). The DDS and FVS were positively correlated with thenutrient adequacy ratio (NAR) and mean adequacy ratio. The NAR is the ratio of intake of a particular nutrient as compared to its recommended dietary allowance. The Mean Adequacy Ratio (MAR) is calculated as an average of NARs of the nutrients considered in a study, divided by the number of nutrients.

L. He, et.al [5], household diversity is important as it reflects the accessibility of food to the household. Socioeconomic status, family size, occupation and education,and geographical location are some of the factors that influence food security of households. For the HDD, twelve food groups were considered namely Cereals, Roots, and tubers. Vegetables, Fruits, Meat, poultry, offal, Eggs, Fish and seafood, Pulses, legumes, nuts, Milk and milk products, Oils/fats, Sugar/honey, and Miscellaneous for assessing household diversity. If food from a particular food groupis consumed by the family, a score of one is assigned. Thus, the maximum possible score would be 12 and the minimum score would be '0'. The HDD can be calculatedfor one household and a mean household diversity score for a study group can be calculated by adding the HDD score of each household divided by the number of households.

H. Hu, et.al [6], associations between household consumption and expenditure may be looked at to get a fuller idea of household dietary diversity and its determinants for a study group. The target cut-offs for minimum HDD can be taken as the average dietary diversity of 33% of households with the highest diversityor the HDD scores of the richest 33% of the households in the study group. The HDDS can be used along with other indicators of household food security. The limitations of HDDS are that the scores will not reflect the diversity of individual family members and food distribution within the family and due to the lack of universal cut-offs, it is difficult to classify households with sufficient and insufficientdietary diversity.

R. Jaswanthi, et.al [7], assessed the micronutrient adequacy in 3704 non- pregnant, non-lactating women of childbearing age using the Minimum Dietary Diversity for Women (MDD-W) index from a household-based, cross-sectional survey comprising data from eight Latin American countries. Ten macronutrients, eight minerals and 10 vitamins were estimated from the 24-hour recall. Nutrient Adequacy Ratios (NAR) was calculated for 17 of the 18 micronutrients considered. They found that the MDD-W associated well with the NAR for most of the micronutrients and with the consumption of food from healthy food groups.

K. Moumane, et.al [8], they found lower dietary diversity scores in women from low socio-economic strata with higher intake of foods from cereals and starchy vegetables and low intakes and diversity in consumption of nuts, fruits and vegetablesthan women whose diets were diverse. However, no differences were seen in the nutritional status of women with high and low diet diversity. In another study where the MDD-W was modified and used for assessment of diet diversity in rural adolescents in eastern Uganda, the index was able to indicate the low dietary diversityas well as dietary transition in the group. Greater consumption of fats and oils, sweetened beverages and cereals and low intakes of animal foods, fruits and vegetables were seen. The authors attributed the low dietary diversity to three main factors namely socio-economic status, adolescents living with single parents or guardians and dependency on household meals.

Kaggle[9], Kaggle is a platform specifically designed for data science and machine learning enthusiasts. It offers a unique combination of features that make it a valuable resource for the community.The Fruits-360 dataset is a large collection of images containing various fruits and vegetables. It's available for download on the Kaggle website. In the dataset "Fruits-360" there are total '90,483' images with training set (67,692) and test set (22,688) with 131 different types of classes.

Python[10], Python is a well-established and widely used programming language, we used Python 3.8.0

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Version, It's available for download on the python.org website. It's the official website for the Python programming language. It provides a wealth of information about python and Python 3.8.0 introduced better type hints, making code more readable and maintainable. This helps static type checkers identify potential errors and improves code clarity for developers. Dictionary Merging (|= operator) this can be especially useful when working with data manipulation tasks. Assignment expressions allow for concise value assignment within expressions. This can make code more compact and easier to read, especially for complex operations. Improved f-strings, This f-strings gained support for formatted string literals within parentheses, enhancing code readability. This allows for more flexible string formatting within expressions. Positional-only arguments provide a way to enforce specific argument order in function definitions. This can improve code clarity and prevent errors caused by incorrect argument ordering. Python 3.8.0 also introduced various performance optimizations, leading to faster code execution and memory usage in some cases.

3. PROPOSED METHODOLOGY

RNN + CNN model described in the abstract integrates Recurrent Neural Network (RNNs) and Convolutional Neural Networks (CNNs) for a comprehensive food recognition and dietary assessment system. It employs CNNs for feature extraction and food food item classification, while RNNs capture temporal dependencies in meal sequences. The model also utilizes Region Proposal Network (RPN) techniques to identify food regions, generating detailed dietary reports by estimating nutritional content.

Hybrid CNN with RNN

A Hybrid Convolutional Neural Network (CNN) with Recurrent Neural Network (RNN) combines the strengths of both architectures for sequential data processing tasks.In this hybrid model, the CNN component extracts spatial features from input data, while the RNN component captures temporal dependencies within sequential data. Thisarchitecture is particularly well-suited for tasks such as video analysis, natural language processing, and time series prediction. By leveraging the hierarchical feature learning capabilities of CNNs and the sequential modeling capabilities of RNNs, the hybrid model can effectively handle complex data structures and capture both spatial and temporal dependencies. However, designing and training such hybrid architectures require careful consideration of architecture design, parameter tuning, and computational resources.

Deep Learning methods for food detection

Nowadays there are many methods to build a new Deep Learning model with specific target. These methods are based on 3 strategies: building and developing new architecture for solving a problem; applied transfer learning and fine tuning on pre-trained models with new domain; and using deep learning platforms which provide deep learning models pre-trained with large dataset; hence it can be used with many purposes.

Food Image Dataset

Regardless of approaches, CNN always requires sufficient data, even large datasets to build an efficient model and avoid over fitting which usually causes by small dataset. As a result, the model only works with that small data and it has not clue when interact with practical data. Though the development of AI technologies, there are limitations on the datasets about nutrition contents.

Name	Classes	Images	Year	Description
UECFOOD-100	100	14,461	2012	Focus on popular foods in Japan
UECFOOD-256	256	31,651	2014	Focus on popular foods in Japan
UECFOOD-101	101	101,000	2015	General Food Categories
UMPCFOOD-101	101	100,000	2015	General Food Categories
VIEROFOOD-172	172	110,421	2016	General Food Categories
FOOD524DB	524	247,636	2017	General Food Categories

FOOD-101N	101	310,000	2018	General Food Categories
FRUITS-360	131	90,380	2021	General Food Categories

Table: 3.1 This represents Food Image Datasets with different categories

The above Table:3.1 gives the representation of Food Image Datasets with different categories. It delves into critical aspects of these datasets, providing insights valuable for researches and practitionetrs in computer vision and Food Recognition.

Class Diversity: This column details the number of distinct food categories within each dataset. A higher class diversity indicates a dataset's ability to represent a wider variety of food items.

Image Volume: This column specifies the total number of images included in each dataset. Larger Images columes often translate to more robust training for machine learning models.

Year of Creation: This column indicates the year when each dataset was first introduced. It can be helpful in understanding the evolution of food image datasets over time.

Food Category: This column classifies the food items depicted in each dataset. This categorization can be instrumental in selecting appropriate datasets for specific tasks, such as food classification or ingredient recognition.

In this model, we are using the Dataset of Fruits-360. It is a widely used dataset designed for Image Classification tasks, particularly focusing on Fruit Recognition. It offers a collection of Images featuring various fruits, categorized into distinct classes. Here's a breakdown of key aspects that make it valuable for training models:

Rich Variety of Fruits (Classes): Fruits-360 boosts a substantial number of classes, ranging from common fruits like Apples and Oranges to more exotic ones like rambutan and kiwi fruit. This diversity allows the model to learn and distinguish between a broad range of Fruits.

Standardized Image Format: The images in Fruits-360 are usually pre-processed to a uniform size (often 100*100 pixels), simplifying the image ingestion process for the model.

Diagram of the Model Processing

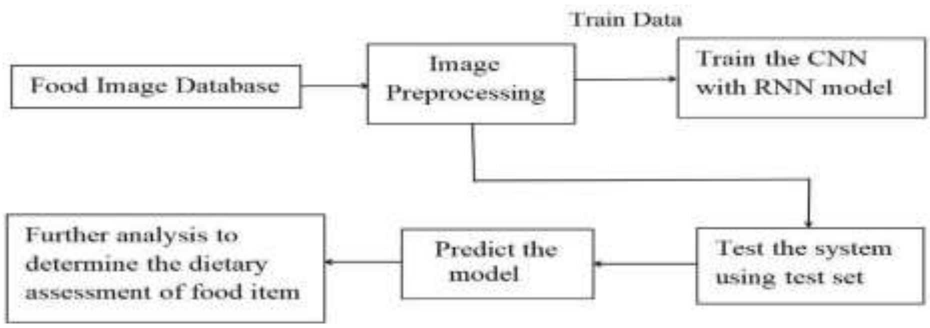

Fig:3.2 Diagram of Processing steps

From the Fig:3.2 shown as the following steps

Food Image Dataset: This block represents the source of Food Images used to train the model. It likely contains a collection of digital images categorized into various food classes.

Preprocessing: Images from the database are often preprocessed before being fed into the model. This might involve resizing the images to a uniform size, converting them to a uniform size, converting them to a specific colour format or applying normalization techniques to ensure consistency.

Train Data: A subset of images from the dataset is designed as the training data. The model is exposed to this data and its internal parameters are adjusted to minimize classification errors on the training sets.

Train the CNN with RNN model: This is the core step where the model learns to classify food images. The CNN is likely responsible for extracting features from the images such as shapes, colors and textures. The RNN might then process these features sequentially to capture contextual information and make a final

prediction about the food category.
Test Data: A separate set of images from the database is used for testing the model's performance. The model is evaluated on its ability to accurately classify images it has nor previously encountered.
Predict the model: Once trained, the model can be used to predict the food category of new images it has not seen before.
Further analysis to determine the dietary assessment of Food Item: After the model predicts the food item in image, this step suggests an additional analysis might be performed to assess the nutritional content of the identified food item. This could involve consulting a Food Database or using a separate model trained for Nutrient Estimation.

4. RESULTS

The "Fruits-360" dataset is a large collection of images containing various fruits and vegetables. It's available for download on the Kaggle website. In the dataset "Fruits-360" there are total '90,483' images with training set (67,692) and test set (22,688) with 131 different types of classes.
In this project, we used loss= categorical cross entropy and metrics=accuracy. The number of 'Epochs' used is 5. The results obtained are presented in Table:4.1

Epoch	Training Time per step	Loss	Accuracy
1	2201s 15s/step	1.0308	0.7252
2	84s 587ms/step	0.1702	0.9432
3	83s 582ms/step	0.1017	0.9633
4	83s 583ms/step	0.0632	0.9797
5	83s 583ms/step	0.0396	0.9871

Table:4.1 Model Accuracy

The above Table: 4.1 shows the representation of Accuracy of the Model, Here is the breakdown of each and every term in the given Table 4.1
Epoch: An epoch refers to one complete pass through the entire training dataset.During each epoch, the model is exposed to all the training examples and updates its internal parameters based on the patterns it learns. In the table, we can see five epochs represented bythe numbers 1 through 5 in the "Epoch" column.
Training Time per step: This metric refers to the amount of time it takes toprocess a single batch of data within an epoch. A batch is a smaller subset of the training data that is fed into the model at each update. The "Training Time per step" column shows the time taken in seconds for each step.
Loss: The loss refers to how well the model is performing on the training data. It's a numerical value that indicates the difference between the model's predictions and the actual values. The goal is to minimize the loss function during training. In thetable, we can see the loss values under the "Loss" column.
Accuracy: Accuracy is a metric used to evaluate how well a machine learning model performs on unseen data. It's usually expressed as a percentage and indicates the number of correct predictions the model makes. The "Accuracy" column shows the accuracy of the model on the training data after each epoch. We trained our model with Hybrid CNN with RNN using the Dataset "Fruits-360"..By using the Strengths of CNN and RNN model got the Accurate Accuracy of "0.9871"and minimum loss of "0.0396".

Imagine a powerful learning model, fine-tuned for optimal performance. This model can be integrated into a mobile app or a web application, allowing users to interact with it through an API (Application Programming

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Interface). With this app, users can simply snap a picture of their food. The model will then analyze the image, recognize the food item, and provide them with a wealth of nutritional information. In essence, this mobile application is designed to empower users, including patients, to identify their food choices and gain valuable insights about their nutritional content. The app achieves this by leveraging a specialized “Hybrid Convolutional Neural Network (CNN) with Recurrent Neural Network (RNN) model”, which has been trained to recognize a vast range of 131 different food items.

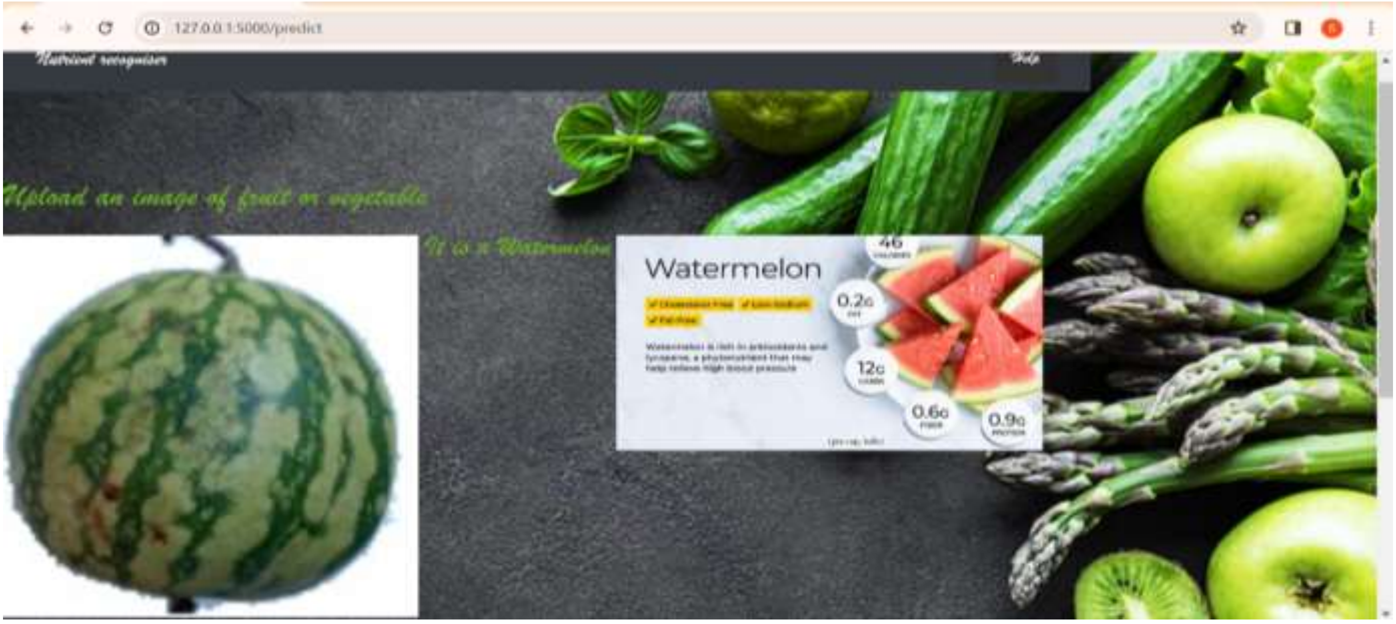

Fig: 4.2 Example of Food Classification Interface

The above Fig: 4.2 states that when we give an input at a place of “Upload an Image of fruit or vegetable” then it detects as the ouput “It is a Watermelon” and gives the picture of ‘Nutrient Estimation’ of detected output Food Item.

The picture of ‘Nutrient Recogniser’ of predicted Item as “It is a Watermelon” describes that Watermelon is a Cholesterol-Free, Low-Sodium, Faat-Free and also represents that Watermelon is rich in antioxidants and lycopene, a phytonutrient that may help relieve high blood pressure. It also describes that ‘per cup, balls’ (quantity) it has ‘46 calories’, ‘0.2 grams of Fat’ , ‘12 grams of Carbohydrates’, ‘0.6 grams of Fiber’, ‘0.9 grams of Protein’.

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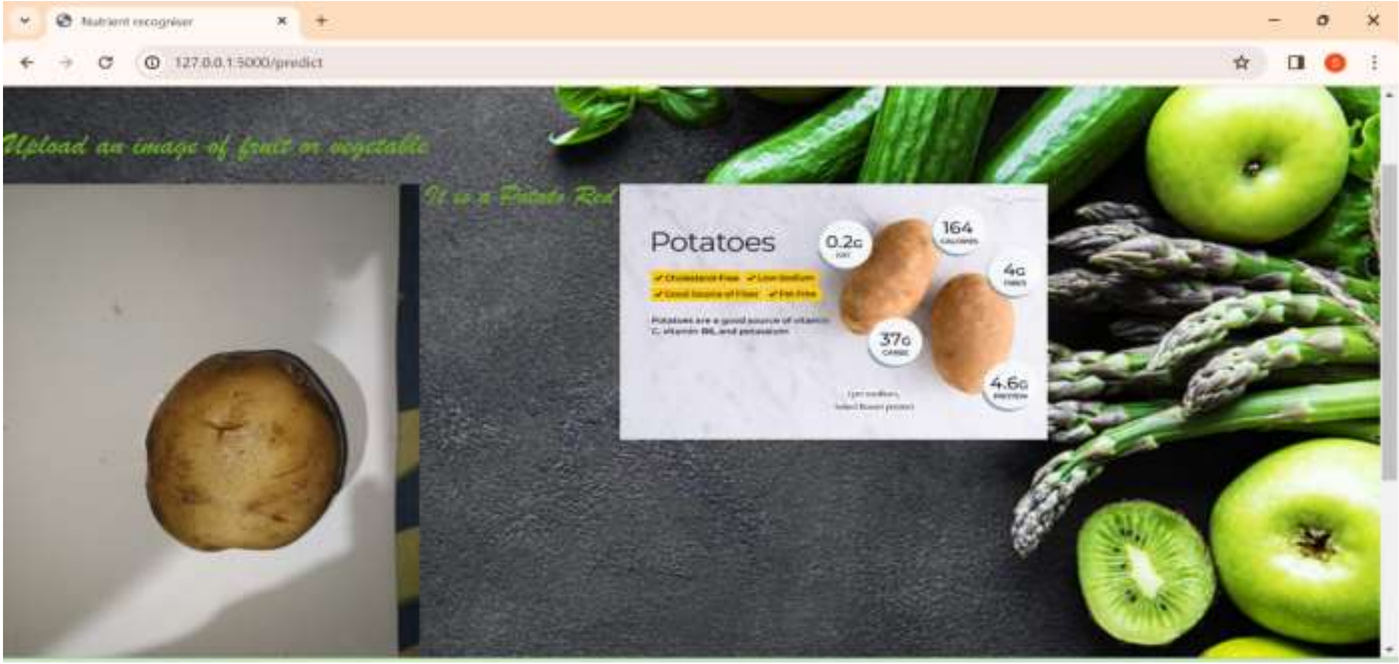

Fig: 4.3 Another Example of Food Classification Interface

The above Figure:4.3 describes that

In this project, we also tried the input with “Real Time Image”, and when we give Input as Potato then it detected as “It is a Potato Red” with the Nutrition Estimation of predicted Food Item.The picture of ‘Nutrient Recogniser ’ of predicted Item as “It is a Potato Red” describes that Potato Red is a Cholesterol-Free, Low-Sodium, Faat-Free and Potato Red is a Good Source of Fiber and also represents Potatoes are a good source of vitamin C, vitamin B6 and potassium.

It also describes that ‘per medium, baked Russet potato’ (quantity) it has ‘164 calories’, ‘0.2 grams of Fat’, ‘37 grams of Carbohydrates’, ‘4 grams of Fiber’, ‘4.6 grams of Protein’.

Food Item	**Quantity**	**Proteins (in gms)**	**Calories (in cal)**	**Carbohydrates (in gms)**	**Fats (in gms)**	**Fibers (in gms)**
Apple Red 1	Per 200g	0.5	104	27.6	0.3	4.8
Watermelon	Per cup	0.9	46	12	0.2	0.6
Pomegranate	Per 282g	4.7	234	29	3.3	11.3
Potato Red	Per medium	4.6	164	37	0.2	4
Mango	Per cup	1.4	99	25	0.6	2.6
Orange	Per 140g	1.3	73	16.5	0.2	2.8
Strawberry	Per cup	1	49	11.7	0.5	3

Avocado	Per 120g	4	322	17	29	13

Table:4.4 Example of Nutrition's Information Interface

In the above Table:4.4 that a balanced diet is essential for optimal health and nutrition. Proteins, carbohydrates, and fats are the three primary macronutrients essential for human health. Proteins are the building blocks of the body, essential for tissue growth, repair, and maintenance. Carbohydrates provide energy and support cellular functions, while fats are essential for physiological functions like insulation andhormone production. A balanced intake of these macronutrients is crucial for optimal health and nutrition. A well-rounded diet with nutrient-dense foods and moderate consumption of processed foods can help maintain a healthy weight and reduce the riskof chronic diseases. Individuals' nutritional needs vary, so customizing macro nutrient intake is key to achieving optimal health outcomes. By prioritizing nutrient-dense foodsand mindful eating habits, individuals can optimize their nutritional intake and enhancetheir quality of life. in above table we got an output of AppleRed-1, Watermelon, Pomegranate, Potato Red and Mango, Orange, Strawberry, Avocado.

5. CONCLUSION

In conclusion, the rich culinary landscape of India, characterized by diverse cuisinesacross communities and regions, necessitates a nuanced approach to understanding dietary patterns and their correlation with the escalating prevalence of non- communicable diseases (NCDs). Recognizing the pivotal role of nutrition, the presented study introduces "DeepFood," a robust deep learning system poised to revolutionize nutritional awareness. Through meticulous evaluation on established food image datasets, DeepFood consistently outperforms various deep learningmodels, demonstrating unparalleled accuracy and efficiency in food item recognition. The system's reliability underscores its potential as a cutting-edge tool for addressing modern nutritional challenges. In the context of India's dietary diversity, DeepFood emerges as a promising advancement, empowering users with comprehensive insights into portion estimation and calorie counting, facilitating informed dietary decisions.

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