

# An Artificial Intelligence-Based System to Assess Nutrient Intake for Hospitalized Patients

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## Abstract

Reducing the risk of disease-related malnutrition requires routine monitoring of nutritional intake in hospitalised patients. There is still a definite need for a more dependable and totally automated way to estimate nutrient intake, since this might increase data accuracy and lessen the burden on participants as well as health expenditures. In this research, we offer an innovative artificial intelligence (AI) method that uses simple RGB Depth (RGBD) picture pair processing to estimate nutritional intake effectively. The system contains a unique multi-task contextual network for food segmentation, an algorithm for 3D surface generation, and a few-shot learning-based classifier for food identification. This enables entirely automated calculation of the nutritional intake for each meal via the sequential segmentation, identification, and estimation of the eaten food volume. A new database specifically created for the system's development and testing, complete with 322 meals' nutritional information and photos of each, has also been built. The predicted nutritional intake outperforms currently available methodologies for nutrient intake evaluation, according to experimental data, which reveal that it is well linked (> 0.91) to the ground truth and exhibits extremely modest mean relative errors ( 20%).

**Keywords:** Novel AI-based automatic system & ResNet , Image recognition, A Multi-Task Contextual Network (MTCNet)

## I. Introduction

Hospitalized patients' MALNUTRITION is a dangerous disease that raises the risk of hospital infections, mortality, morbidity, prolonged hospital stays, and additional healthcare costs. Studies carried out among hospitalised patients in various nations have shown that the incidence of inpatient malnutrition may be over 40% on average. Thus, it is crucial for both hospitalised patients and societal medical systems to maintain adequate nutritional condition. It is critical to frequently assess the daily dietary intake of hospitalised patients since inpatient malnutrition is mostly due to inadequate detection and monitoring of nutritional intake. This has historically relied on non-automated semi-automated methods that are either time-consuming, costly, or prone to mistake, such food weighing, visual estimates, or digital photography. As a result, there is still an unmistakable need for an accurate and straightforward method to determine nutritional consumption. It is now possible to assess food items via a food photograph thanks to the development of AI-based image processing techniques. This opens up the possibility of totally autonomous nutritional intake calculation. AI-based nutritional evaluation systems, such Im2Calories for estimating calories, have recently been suggested. The systems analyse food photos in three steps: segmenting the food into individual components, identifying the food, and estimating the amount of the meal. As a result, the food nutrition database may be used to compute nutrient content. While these pioneering experiments have shown that utilising AI to assess food consumption is feasible, there is still a need to further enhance performance in terms of estimate accuracy and the number of supported food categories. The challenge, however, is that the quality and amount of the food picture collection for nutritional intake evaluation are naturally constrained by the complex annotation requirements. This makes it more difficult to apply certain cutting-edge AI algorithms for food picture analysis, since these algorithms significantly rely on having a huge database. As a result, we need a special database and related AI algorithms that can be modified to work with less training data. As an extension of our previous work, we present an AI-based, totally autonomous system in this study for

monitoring hospitalised patients' nutritional intake by analysing RGB-D picture pairs taken during a meal. Based on 322 food trays (meals) that the central kitchen of Bern University Hospital produced for hospitalised patients, a new database of food photos with related nutritional information and recipes is generated. A total of 1281 food items from 521 food categories are included in the database. Many AI-based methods to predict nutritional consumption are designed, developed, and validated using this information. 1) A Multi-Task Contextual Network (MTCNet), which uses a pyramid architecture for feature encoding and a newly created CTLayer to give contextual information between meals and serving plates, is used for food segmentation; 2) a revolutionary few-shot learning-based classifier [17] for food identification that is innovative in terms of design. A 3D surface building method is used to estimate the amount of food eaten, the food identification model is trained inside the meta-learning framework [17] and makes use of the transferred weight, and a nutrient intake calculator connects the ingested volume, food type, and recipe. The findings of the experiments show extremely high correlation coefficients ( $r > 0.91$  for calories and all nutrient types;  $p < 0.001$ ) and very low mean relative errors (20% for calories and all nutrient types) between the software forecast and the actual data. To the best of our knowledge, this performs better than earlier research and provides a summary of the suggested system. The RGB-D picture pairs that were recorded during a daytime meal are the system's inputs. The system's outputs include estimates of nutritional consumption as well as food segmentation, identification, and volume for examples of daily meals.

## II Literature Survey

**Title:** Prevalence of Malnutrition Risk and the Impact of Nutrition Risk on Hospital Outcomes: Results From nutrition Day in the U.S.

**Author:** Abby C. Sauer, MPH, RD1; Scott Goates, PhD1; Ainsley Malone, MS, RD

**Year:** 2019.

**Description:** Hospitals in the United States lack reliable data on the link between food consumption and outcomes, and estimates of malnutrition risk vary widely (U.S.). The purpose of this research was to use the nutrition Day in the U.S. dataset to calculate the risk of malnutrition and assess the relationship between food consumption and mortality. Methods: This research included all adult patients treated at the participating institutions between 2009 and 2015. Malnutrition risk prevalence was calculated by comparing responses to the Malnutrition Screening Tool (MST). After accounting for age, mobility, and other disease-related characteristics, the influence of nutrition risk and food consumption on 30-day in-hospital mortality was assessed using Fine and Gray competing-risk analysis with clustering. A total of 9959 adult patients from 601 different wards were analysed. 32.7 percent of the population was at risk for malnutrition, as defined by an MST score of 2. A third or fewer of patients on nutrition Day finished their servings. Patients who ate only a quarter of their meal compared with those who ate the full meal had a hazard ratio of 3.24 (95% CI: [1.73, 6.07]; P-value 0.001) for hospital mortality, and patients who ate nothing despite being allowed to eat had a hazard ratio of 5.99 (95% CI: [3.03, 11.84]; P-value 0.0001). The study's findings, showing almost one-third of hospitalised patients in the United States are at risk for malnutrition, represent the most solid estimate to date. Those who consume less calories have a higher chance of dying. These findings provide insight on the persistent problem of hospital-related malnutrition. Journal of Parenteral and Enteral Nutrition. 2019 Jan 9.

**Title:** Image-Based Estimation of Real Food Size for Accurate Food Calorie Estimation.

**Author:** Takumi Ege, Yoshikazu Ando, Ryosuke Tanno, Wataru Shimoda and Keiji Yanai.

**Year:** 2014.

**Description:** In this publication, we summarise our research on estimating food calories accurately based on images, which includes three previously published studies and two brand new ones: Calorie Cam, a system for estimating the size of real food using a reference object; Region segmentation based food calorie estimation; AR Deep Calorie Cam V2, a system for estimating the size of real food using visual inertial odometry built in the iOS ARKit library; Depth Calorie Cam, which uses the stereo cameras on the iPhone X/XS; and Rice Calorie Cam, which uses rice grains as reference objects. Recently, two novel approaches have been developed that successfully estimate food calories with an error of 10% or less.

**Title:** LOW DOSE ABDOMINAL CT IMAGE RECONSTRUCTION: AN UNSUPERVISED LEARNING BASED APPROACH

**Author:** Shiba Kuanar, Vassilis Athitsos , Dwarikanath Mahapatra, K.R. Rao,

**Year:** 2019.

**Description:** Radiation exposure from medical X-ray CT scans has been linked to an increased incidence of prostate and abdominal malignancies. Low dosage CT scans, on the other hand, may lessen the patient's exposure to harmful radiation. Yet, the radiologist's ability to diagnose and prognosticate is hindered since the lower radiation dosage reduces picture quality for human perception. To de-noise the CT images, we present a GAN-based auto-encoder network in this research. Before restoring CT images from their manifold representations, our network maps the pictures to lower dimensional spaces. By calculating perceptual similarity and learning latent feature maps independently, our reconstruction approach improves accuracy and aesthetic appeal. We also compared the performance of our model to that of preexisting deep learning and iterative reconstruction techniques, and demonstrated its efficacy on a set of CT scans of patients' abdomens. The experimental findings show that our model has better PSNR, SSIM, and statistical characteristics of the image areas compared to the state-of-the-art approaches.

**Title:** An Artificial Intelligence-Based System for Nutrient Intake Assessment of Hospitalised Patients

**Author:** Yoon Ya Lu, Thomai Stathopoulou, Maria F. Vasiloglou, Stergios Christodoulidis, Beat Blum,

**Year :** 2019

**Description:** — Hospitalized patients might greatly benefit from regular food intake monitoring in order to lessen the likelihood of disease-related malnutrition (DRM). Although there are now a number of approaches available for estimating dietary intake, there is a clear need for a more robust and completely automated approach that may increase data accuracy while decreasing participant burden and health care expenses. In this work, we offer a unique AI-based approach for estimating dietary intake merely by analysing RGB depth picture pairs taken before and after a meal. In order to test and improve the system, we used an entirely new database including 322 different meal photos and recipes annotated using cutting-edge techniques. Using this information, a system was built that combines a revolutionary multi-task neural network with an algorithm for building 3D surfaces. Completely automatically estimating nutritional intake for each meal type with a 15% estimate error was made possible by sequentially semantic food segmentation and volume estimation.

**Title:** Foodx-251: a dataset for fine-grained food classification.

**Author:** Parneet Kaur, Karan Sikka, Weijun Wang, Serge Belongie

**Year:** 2019.

**Description:** Food classification is hard because there are so many different types of foods and they look a lot alike. Also, there aren't enough datasets to train the most advanced deep models on. To solve this problem, both computer vision models and datasets that can be used to test these models will need to get better. In this paper, we focus on the second part and introduce FoodX-251, a set of 251 food categories with 158k images collected from the web. We use 118 kimages as a training set and give labels for 40 kimages that have been checked by humans. These can be used for validation and testing. In this work, we explain how this dataset was made and give deep learning models relevant starting points. The FoodX-251 dataset was used to organise the iFood-2019 challenge in the Fine-Grained Visual Categorization workshop (FGVC6 at CVPR 2019) and can be downloaded.

### III Proposed Model

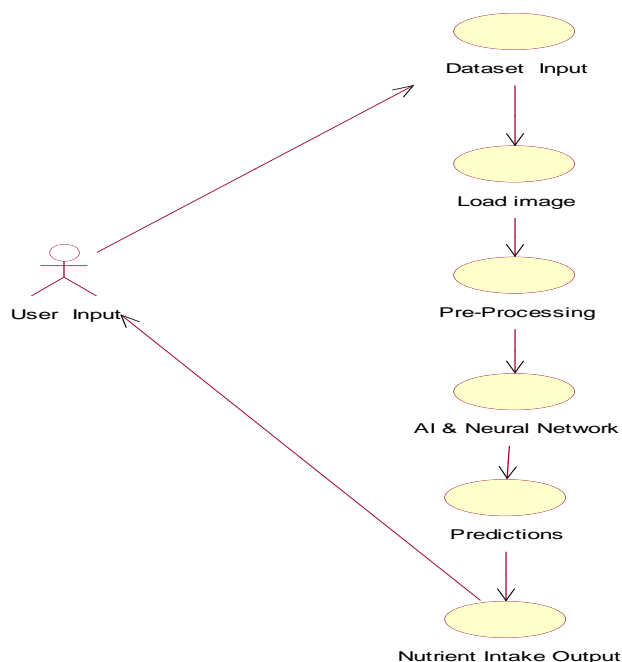
In this paper, we describe the design, development, and testing of a new AI-based automatic system for estimating a hospitalised patient's nutrient intake in a pipeline fashion. Several new approaches are suggested, such as the new multimedia-nutrient combined database that collected data in a real hospital setting, the specially designed MTCNet for food segmentation, and the newly proposed few-shot learning classifier for food recognition. We showed that the proposed algorithms performed better than the state-of-the-art in all ways, and that it would be possible to build an accurate nutrient intake assessment system with only a small amount of training data. We

propose an AI-based, fully automatic system for figuring out how much nutrition hospitalised patients are getting by analysing RGB-D image pairs taken during a day meal. From 322 food trays (meals) made for hospitalised patients by the central kitchen of Bern University Hospital, a new database of food images, nutrition facts, and recipes is made. There are a total of 1281 food items from 521 food groups in the database. This database is used to design, build, and test a number of AI-based algorithms that estimate the amount of nutrients taken in. It uses: 1) a Multi-Task Contextual Network (MTCNet) for food segmentation, which uses a pyramid architecture for feature encoding and a newly designed CTLayer to provide contextual information between foods and serving plates; and 2) a few-shot learning-based classifier for food recognition. The food recognition model is trained with meta-learning and uses the transferred weight; 3) an algorithm for building 3D surfaces.

## IV Result & Discussion

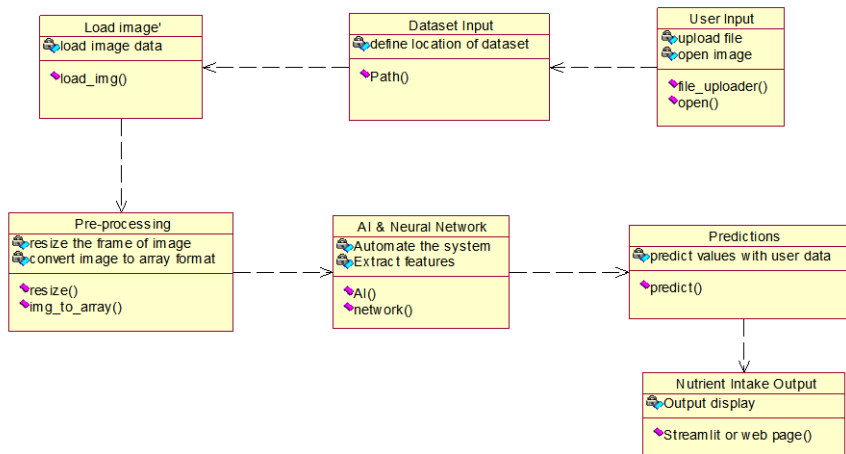
For the purpose of project execution, Design Engineering works with numerous UML [Unified Modeling language] diagrams. A design is an accurate engineering depiction of a future construction. The process of translating requirements into a representation of the programme is called software design. In software engineering, quality is produced throughout the design phase. To correctly transform consumer needs into a final product, use design.

### UML DIAGRAMS



#### 4.2.1. USE CASE DIAGRAM

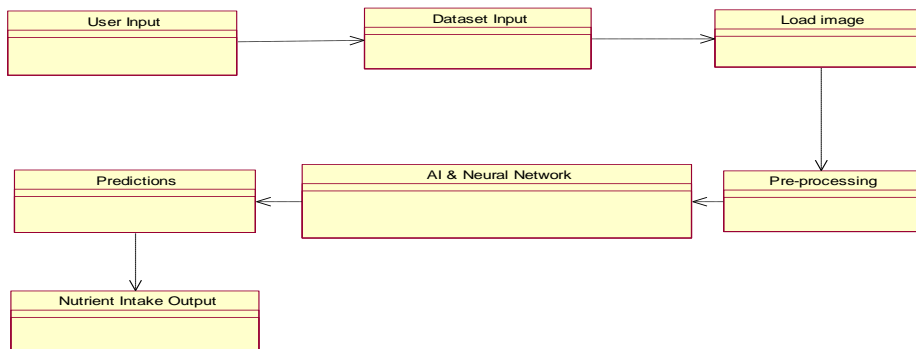
A use case diagram's primary objective is to identify which system functions are carried out for particular actor. The system's actors may be represented by their roles. The user is an actor in the diagram above. To realise the notion, everybody will play a certain role.



### 4.2.2 CLASS DIAGRAM

#### Explanation

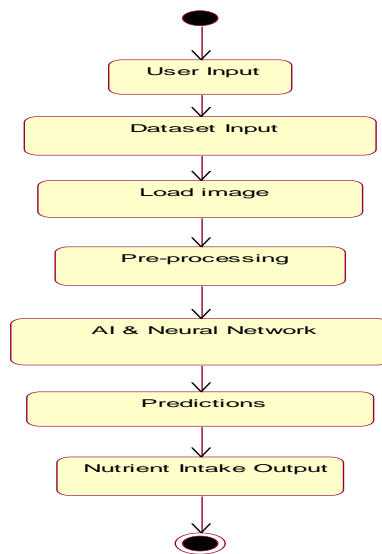
This class diagram shows how the classes' characteristics and methods are connected to one another to carry out security verification. The several classes involved in our project are shown in the diagram up above.



### 4.2.3 OBJECT DIAGRAM

#### Explanation:

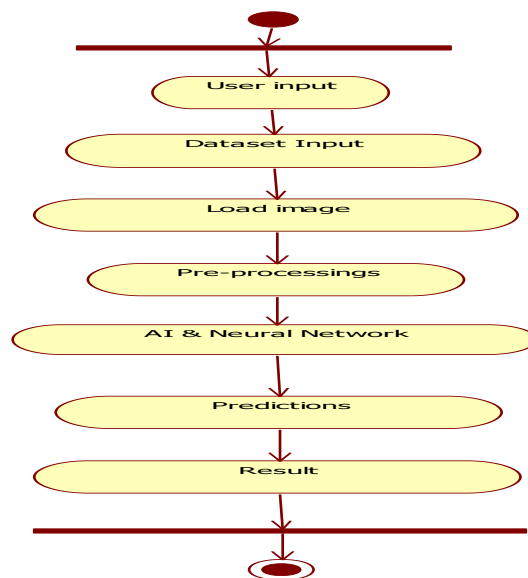
The accompanying diagram illustrates how things move across the classes. A full or incomplete perspective of the structure of a modelled system is shown in this figure. This object diagram shows how classes with attributes and methods are connected to one other to carry out security verification.



#### 4.2.4 STATE DIAGRAM

##### Explanation:

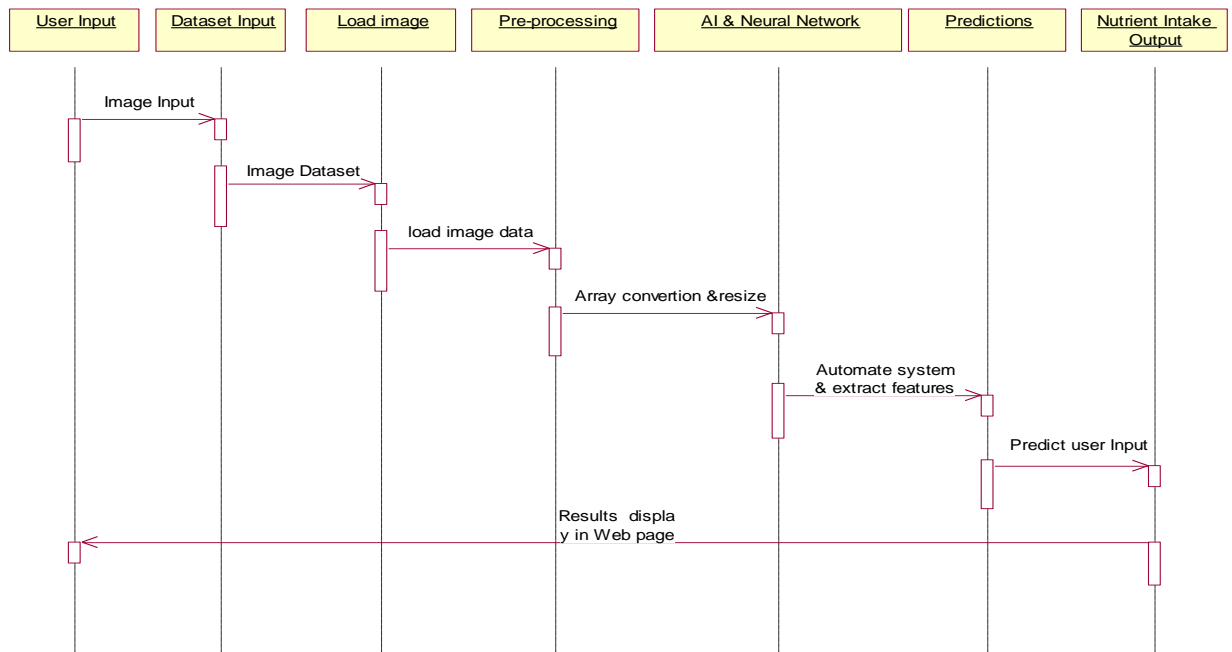
State diagrams, which enable choice, iteration, and concurrency, are a loosely defined diagram to display workflows of progressive activities and actions. State diagrams call for the system being represented to consist of a limited number of states; sometimes, this is the case, and other times, it's only an acceptable abstraction. State diagrams come in a variety of shapes and sizes, each with a distinct meaning.



#### 4.2.5 Activity Diagram

##### Explanation:

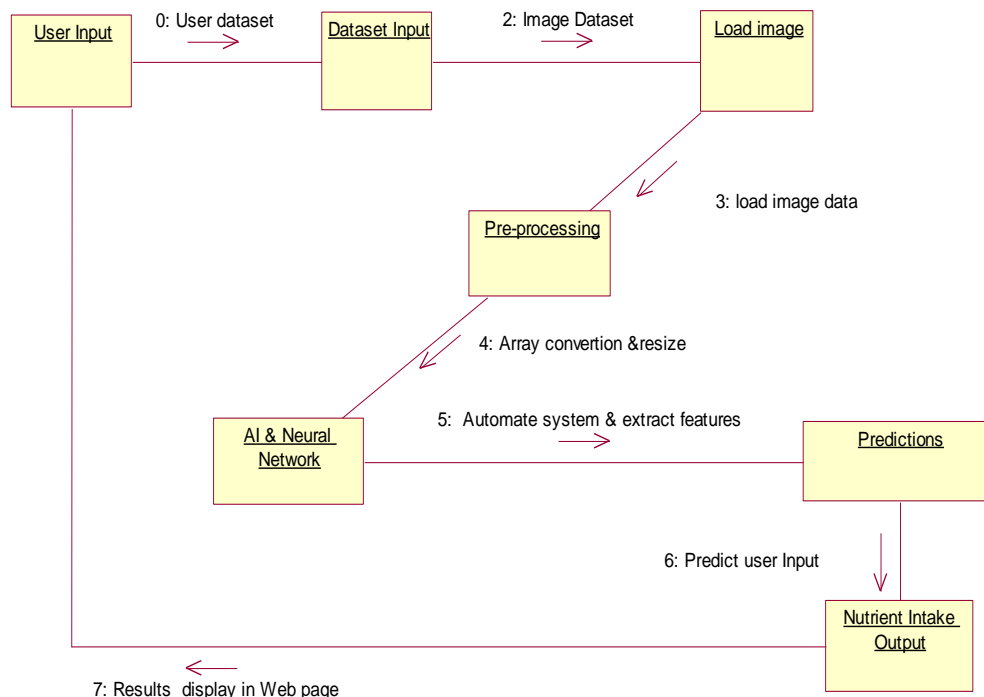
Activity diagrams are visual depictions of processes with choice, iteration, and concurrency supported by activities and actions. Activity diagrams may be used to depict the operational and business processes of system components in the Unified Modeling Language. An activity diagram demonstrates the total control flow.



#### 4.2.6 SEQUENCE DIAGRAM

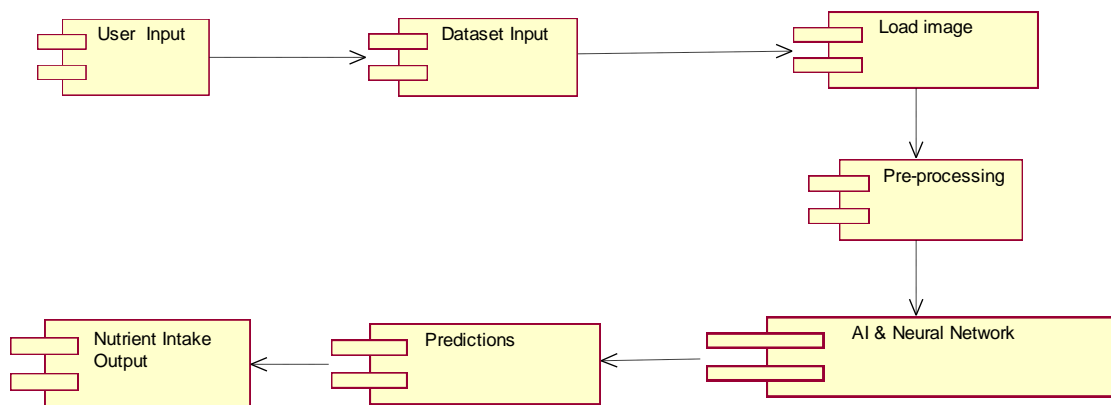
##### Explanation:

In the Unified Modeling Language (UML), a sequence diagram is a kind of interaction diagram that demonstrates how and in what order processes interact with one another. It is a Message Sequence Chart construct. Object interactions are arranged in temporal order in a sequence diagram. It shows the classes and objects involved in the scenario as well as the flow of messages that must be exchanged for the objects to work as intended.



**Explanation:**

An depiction of the links and interactions among software objects in the Unified Modeling Language is a collaboration diagram, also known as a communication diagram or an interaction diagram (UML). While it has been improved as modelling paradigms have changed, the idea is more than a decade old.

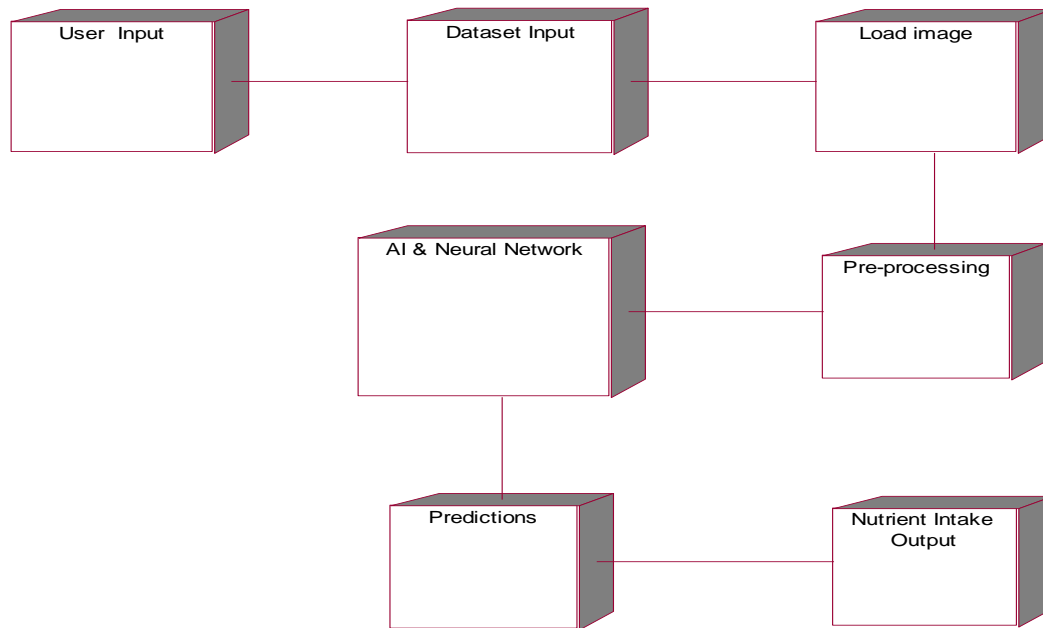


**4.2.7 COMPONENT DIAGRAM**

**Explanation**

A component diagram in the Unified Modeling Language shows how smaller components are connected to create bigger components and/or software systems. They provide as examples of the structure of systems that may be arbitrary complicated. User submits primary inquiry, which is divided into subquestions and sent to data aggregators through data dissemination. Data aggregators are responsible for displaying results to users. Each box represents a component, while the arrows show dependencies.





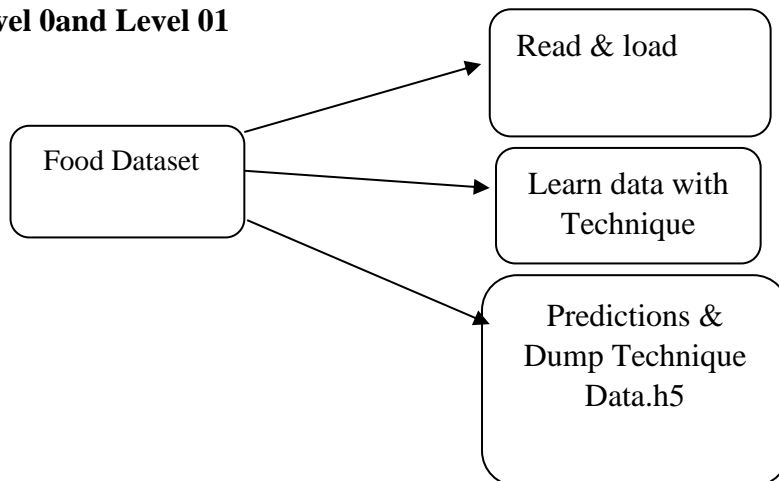
#### 4.2.8 DEPLOYMENT DIAGRAM

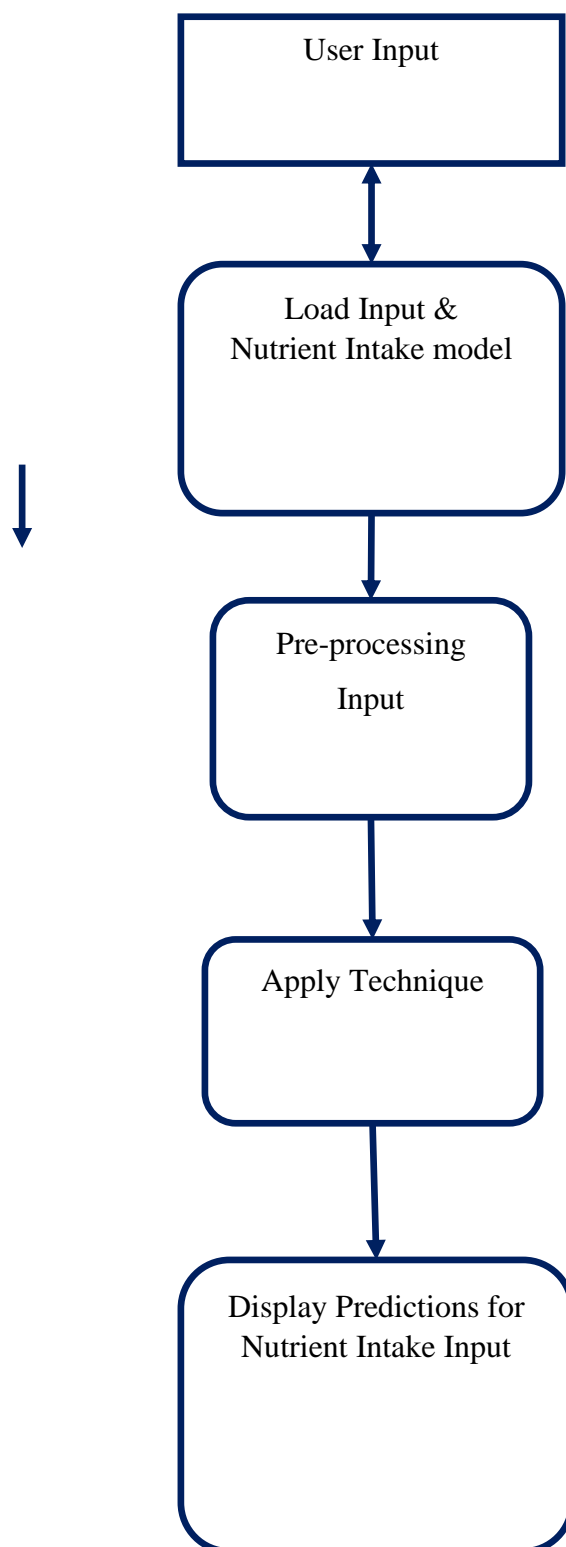
##### Explanation:

A particular kind of diagram known as a deployment diagram identifies the actual hardware that the software system will run on. Moreover, it controls the software's implementation on the underlying hardware. It links system software components with the hardware that will run them.

##### Data Flow Diagram

##### Level 0 and Level 01





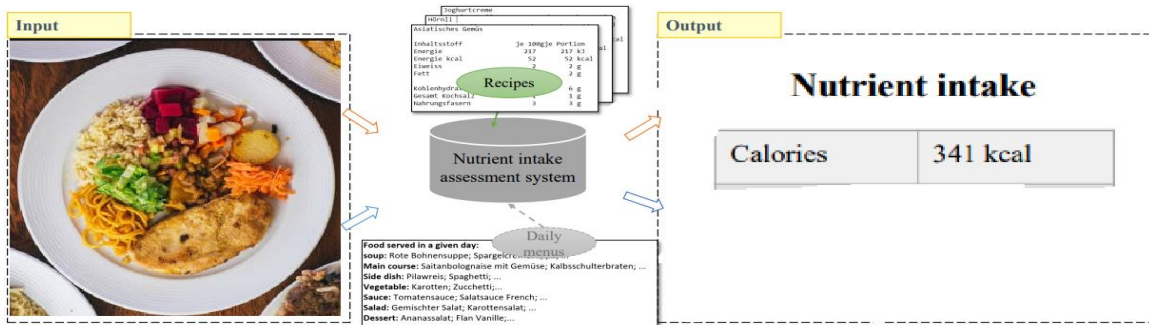


Fig. Proposed Methodology

## Nutrient Intake



## Nutrient Intake..

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## SNAPSHOTS



## Nutrient Intake..


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Nutrient Intake:-

77 calories(Intake)

## Nutrient Intake..

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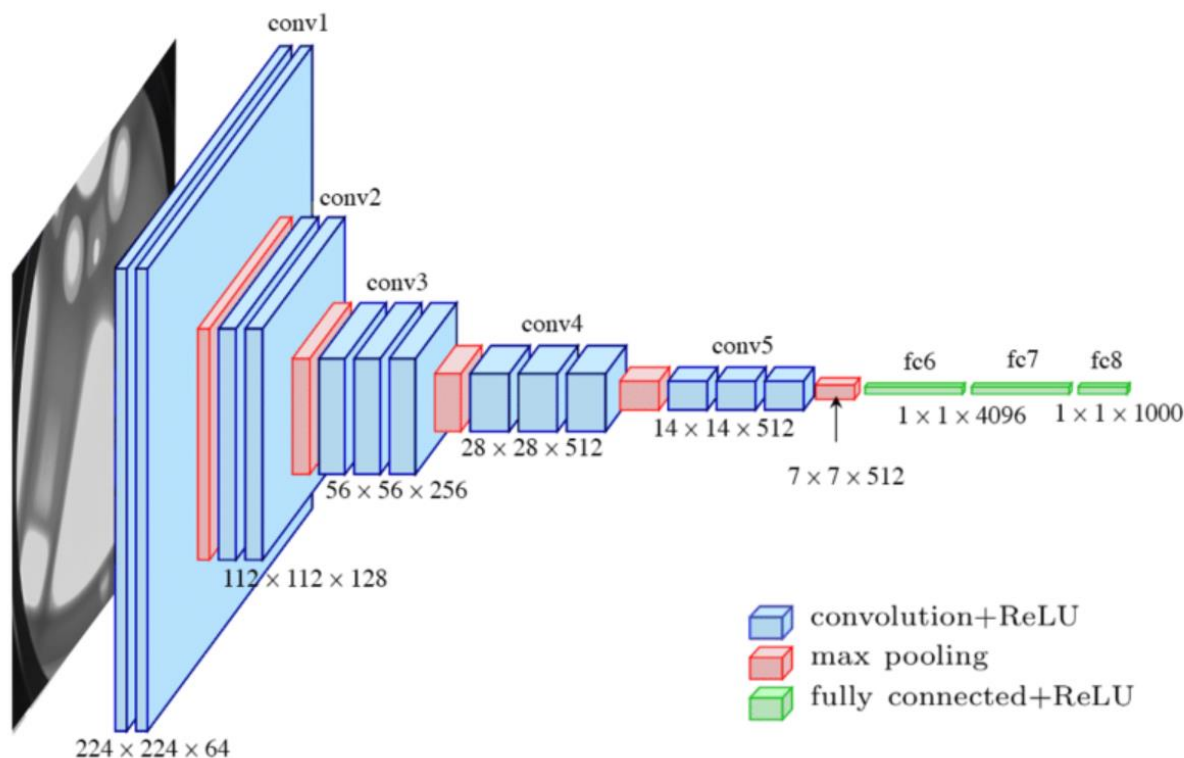
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fast.jpg 353.1KB



Nutrient Intake:-

60 calories(Intake)



## V. Conclusion

In this study, a unique AI-based automated system for calculating nutritional intake for hospitalised patients in a pipeline fashion is designed, developed, and evaluated. The new multimedia-nutrient combination database, the specifically developed MTCNet for food segmentation, and the recently suggested few-shot learning classifier for food identification are just a few of the original ideas put forward. We showed that the suggested algorithms outperformed the state-of-the-art in all areas, along with the viability of the user interface (GUI), including the size and number of the segments, their compactness, etc. Afterwards, each section may be chosen and marked with one of the labels that have already been established by the user. A brush tool with different sizes may also be used to pick or deselect pixels, allowing for more precise selection. Once again, labels may be applied to the chosen pixels. In case of an error, any chosen region may be at any point unlabeled.

## VI Future Scope

the conception, creation, and assessment of an unique AI-based automated system for pipeline-based nutritional intake estimation for hospitalised patients. The new multimedia-nutrient combination database, the specifically developed MTCNet for food segmentation, and the recently suggested few-shot learning classifier for food identification are just a few of the original ideas put forward. We showed that the suggested algorithms outperformed the state-of-the-art in all areas, along with the viability of the user interface (GUI), including the size and number of the segments, their compactness, etc. Afterwards, each section may be chosen and marked with one of the labels that have already been established by the user. A brush tool with different sizes may also be used to pick or deselect pixels, allowing for more precise

selection. Once again, labels may be applied to the chosen pixels. In case of an error, any chosen region may be at any point unlabeled.

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