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SWASTH *: AN INVERSE COOKING RECIPE GENERATION FROM FOOD IMAGES

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Abstract: The three important for every one of us is food, cloth and house. We give the first priority to food. At the same in this fast generation making a food by spending so many hours in the kitchen is a tough task. People are using various food delivery apps like Zomoto, Swiggy, Uber eats and many to get their food. Many restaurants have started takeaways courts to parcel the food items. Behind of every meal there is aprocedure involved in making of it. How to the know the process behind of it. The basic of aim of this paper is to provide a solution to the query. We are introducing an inverse cooking system named it as "Swasth". This system recreates cooking recipes for the given food image. This system provides the ingredients used and then also gives the cooking instructions. Our system uses a unique architecture to forecast ingredients as sets, modelling their relationships without enforcing any order, and then creates cooking directions while concurrently paying attention to the image and its predicted components. We thoroughly test the system on the massive Recipe 1 million dataset and demonstrate that we are able to obtain high quality recipes by utilising both image and ingredients. We also demonstrate that the system is able to produce more compelling recipes than retrieval-based approaches in terms of human judgement.

Keywords: Inverse cooking, CNN, Deep learning, Machine learning.

* Swasth is a hindi word means tasty.

I. INTRODUCTION

In this planet, every one including species needs food to survive. Food gives us a energy. The foodfines our identity and culture. Especially, the youth puts their favourite food items in the social media to say it we ate this food. Recently, the Instagram post #food reads to at least 300 million posts;

We always like to see the pictures of the food. These pictures attracts us to eat. There is also a process involved for every dish and by looking the picture some of us gets a question what isrecipe for this food item. To get a solution of this question, here the software provides a solution.

The three important for every one of us is food, cloth and house. We give the first priority to food. At the same in this fast generation making a food by spending so many hours in the kitchen is a tough task. People are using various food delivery apps like Zomoto, Swiggy, Uber eats and manyto get their food. Many restaurants have started take away courts to parcel the food items. Behindof every meal there is a procedure involved in making of it.

Eating customs and cooking culture have also evolved over time. Nowadays, we frequently eat meals that have been prepared by other parties, such as takeaway, caterers, and restaurants, but traditionally, the majority of meals were produced at home. Because it is difficult to acquire detailed information on prepared meals, it is tough to know exactly what we ingest. We argue that prepackaged meals must be used to infer the components and cooking instructions for inverted cooking systems. Over the past few years, significant progress has been achieved in visual recognition tasks, such as object identification, semantic segmentation, and natural picture classification. When compared to natural picture understanding, however, food recognition presents more difficulties since food and its components have a high intraclass variability and exhibit significant deformations due to cooking.

Ingredients come in a variety of colours, shapes, and textures when they are prepared, which usually obscures their appearance. Additionally, extremely complex reasoning and background information are required for visual ingredient detection. Because of this, food identification is a problem for modern computer vision systems, requiring them to go beyond the apparent and consider prior knowledge to provide high-quality structured food preparation descriptions. Food classification has been a major focus of previous attempts to better understand food. However, in addition to being

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able to recognise the type of meal and its components, a system for full visual food identification should also be able to understand how the food was prepared.

In a cooked dish, ingredients frequently get obscured and arrive in a range of hues, shapes, and textures. Additionally, visual ingredient recognition needs very sophisticated reasoning and prior knowledge. Food identification therefore presents a challenge to the state-of-the-art computer vision systems, forcing them to go beyond the obvious and take into account past knowledge to allow high-quality structured food preparation descriptions.

Traditionally, most meals were made at home, but nowadays, we regularly eat meals made byother sources, such as takeout, caterers, and restaurants. It is difficult to know exactly what we consume because there is little access to specific information about prepared meals. We contend that inverse cooking systems, which can deduce ingredients and cooking directions from a prepared meal, are necessary. Outstanding advancements have been made in visual recognition tasks over the past few years, including object identification, semantic segmentation, and natural picture categorization. When compared to natural picture understanding, however, foodrecognition presents more difficulties since food and its components have a high intraclass variability and exhibit significant deformations due to cooking.

II. RELEATED WORK

Previous efforts on food understanding have mainly focused on food and ingredient categorization.However, a system for comprehensive visual food recognition should not only be able to recognizethe type of meal or its ingredients, but also understand its preparation process. Traditionally, the image-to-recipe problem has been formulated as a retrieval task where a recipe is retrieved from a fixed dataset based on the image similarity score in an embedding space. The performance of such systems highly depends on the dataset size and diversity, as well as on the quality of the learned embedding. Not surprisingly, these systems fail when a matching recipe for the image query does not exist in the static data. The limitation of the existing system are a system for comprehensive visual food recognition should not only be able to recognize the type of meal or its ingredients, butalso understand its preparation process.

The proposed system works like a training will be done using Convolutional neural network (CNN) with recipe details and images and this model can be used to predict recipe by uploading related images and we used 1 million recipe dataset and from this dataset we used 1000 recipes as training entire dataset with images will take lots of memory and hours of time train CNN model.

The benefits of using the proposed system are we present an inverse cooking system, which generates cooking instructions conditioned on an image and its ingredients, exploring different attention strategies to reason about both modalities simultaneously. We exhaustively study ingredients as both a list and a set, and propose a new architecture for ingredient prediction that exploits co-dependencies among ingredients without imposing order. By means of a user study weshow that ingredient prediction is indeed a difficult task and demonstrate the superiority of our proposed system against image-to recipe retrieval approaches.

III. SYSTEM ARCHITECTURE

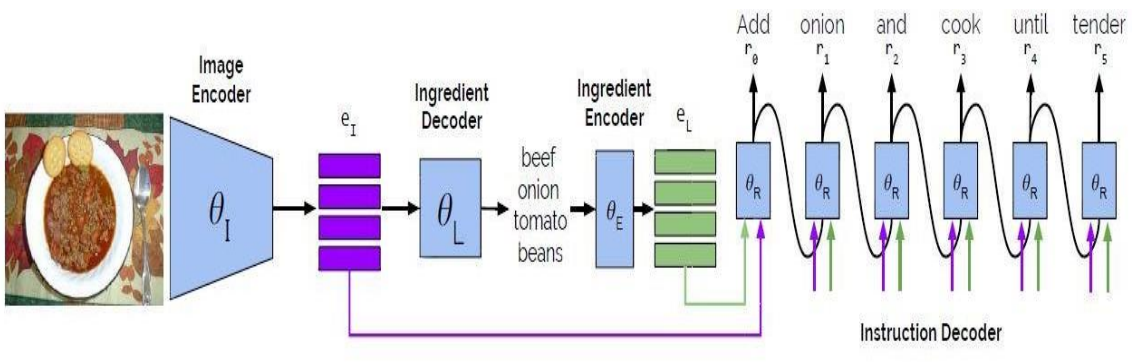

Figure: System Architecture
(Source: https://ai.facebook.com/blog/inverse-cooking/)

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IV. RESULTS

In the implementation part, feature extraction task we tried resnet-50, se-resnet-50 and se-resnet-101. Ingredients extraction task we used word2vec embedding and bi-directional LSTM and instruction retrieval task We used two stage LSTM. We generated a sample dataset and perform different feature extraction algorithm. That contain ingrs.pkl ,instr.pkl and demo images file.From the results , we get se-resnet-101 with higher accuracy than resnet-50 and se-resnet50.

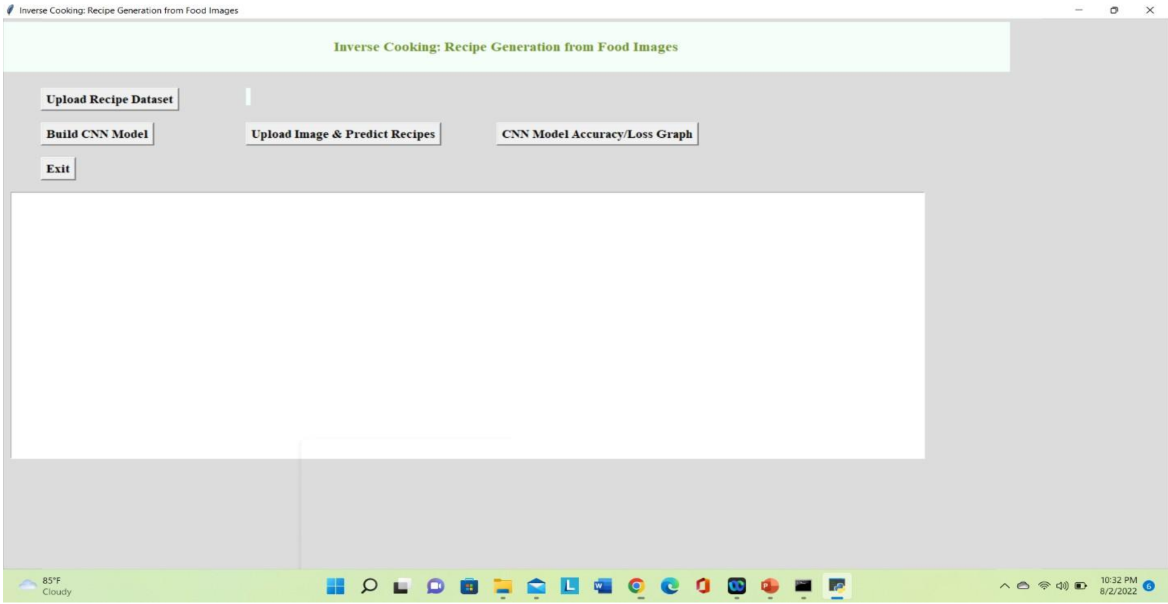

Fig: User Interface Screeb

In above screen click on 'Upload Recipe Dataset' button to upload dataset

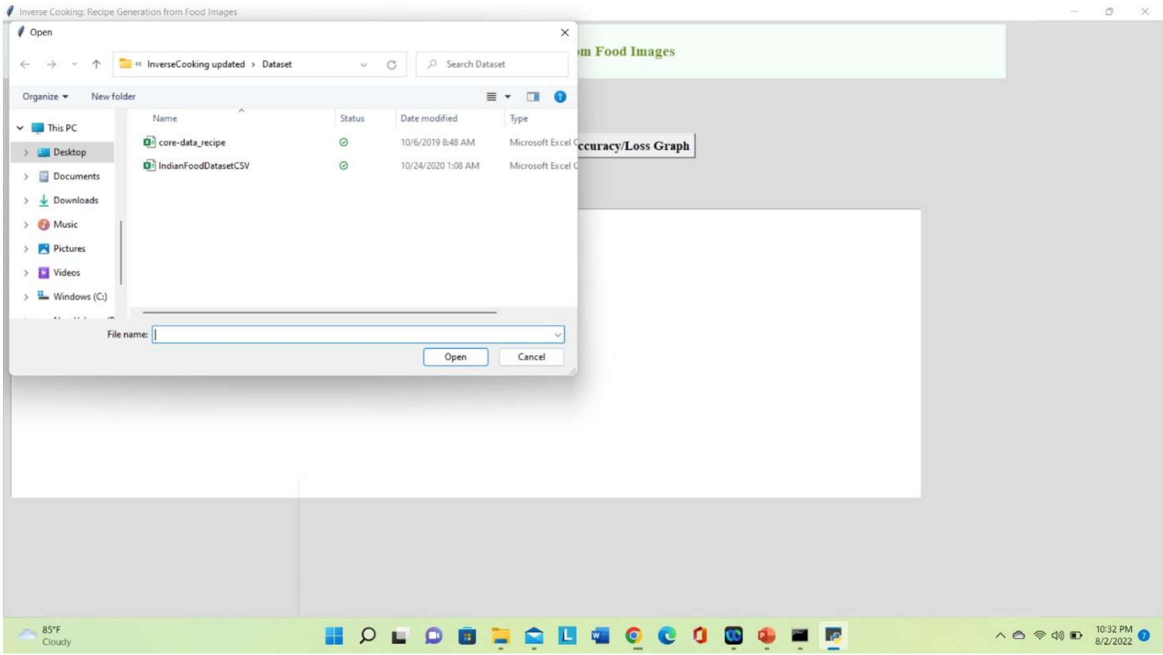

Fig: Upload Dataset

In above screen selecting and uploading recipe dataset and then click on 'Open' button to loaddataset and to get below screen.

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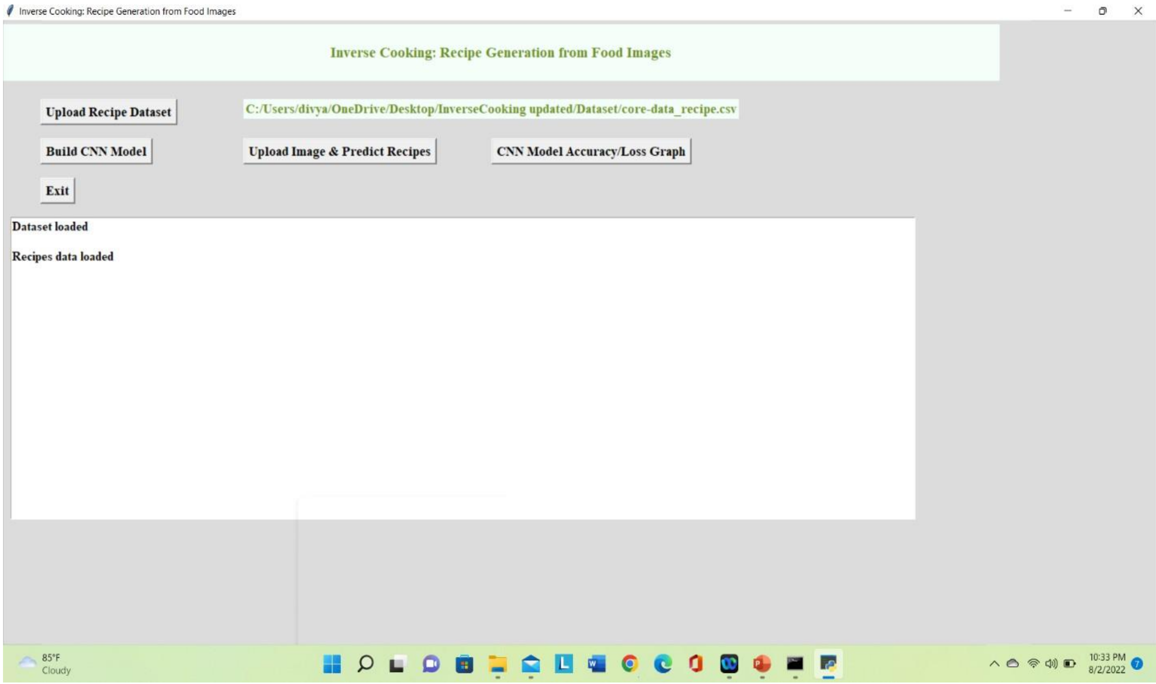

Fig : Build Machine Learning Model

In above screen dataset loaded and now click on ‘Build CNN Model’ button to build CNN onabove dataset.

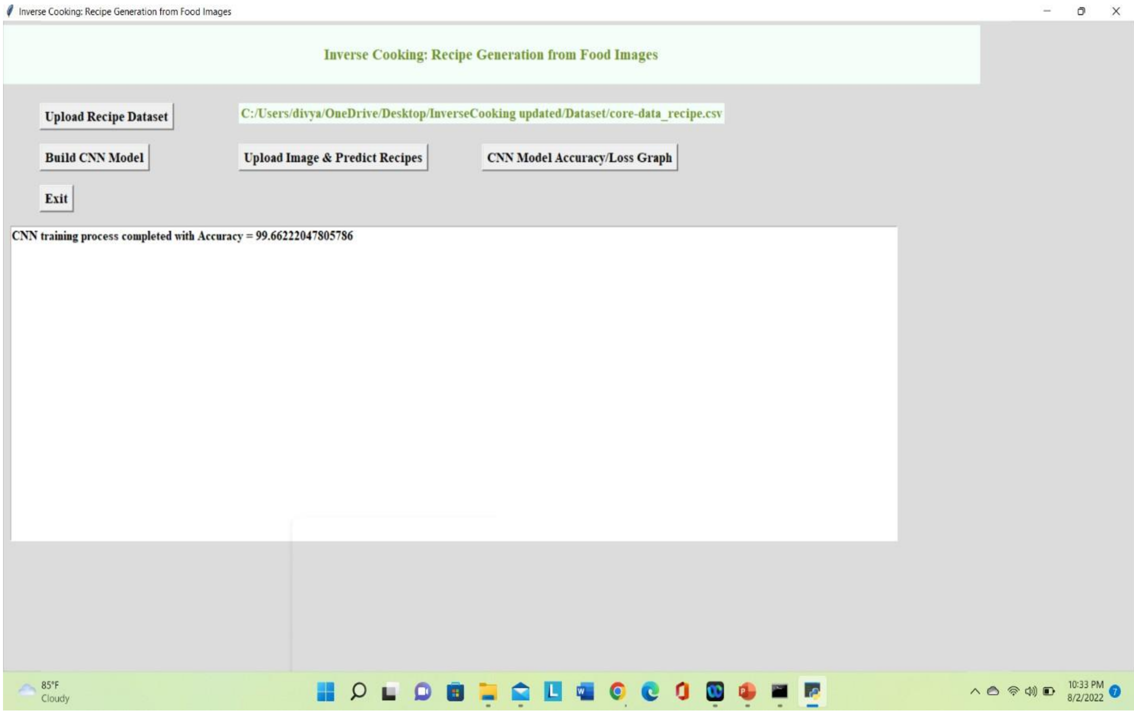

Fig : Model Built

In above screen CNN model generated and we got prediction accuracy as 99.6%. Now click on‘Upload Image & Predict Recipes’ button to upload test images.

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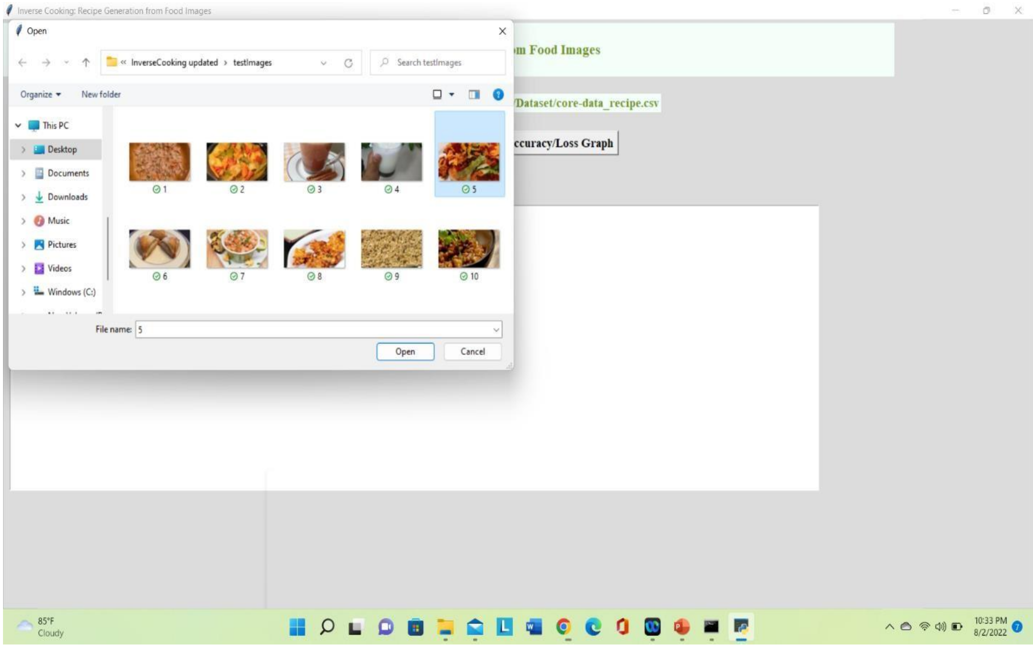

Fig: Select Test Image

In above screen select any image and then click on 'Open' button to get below result.

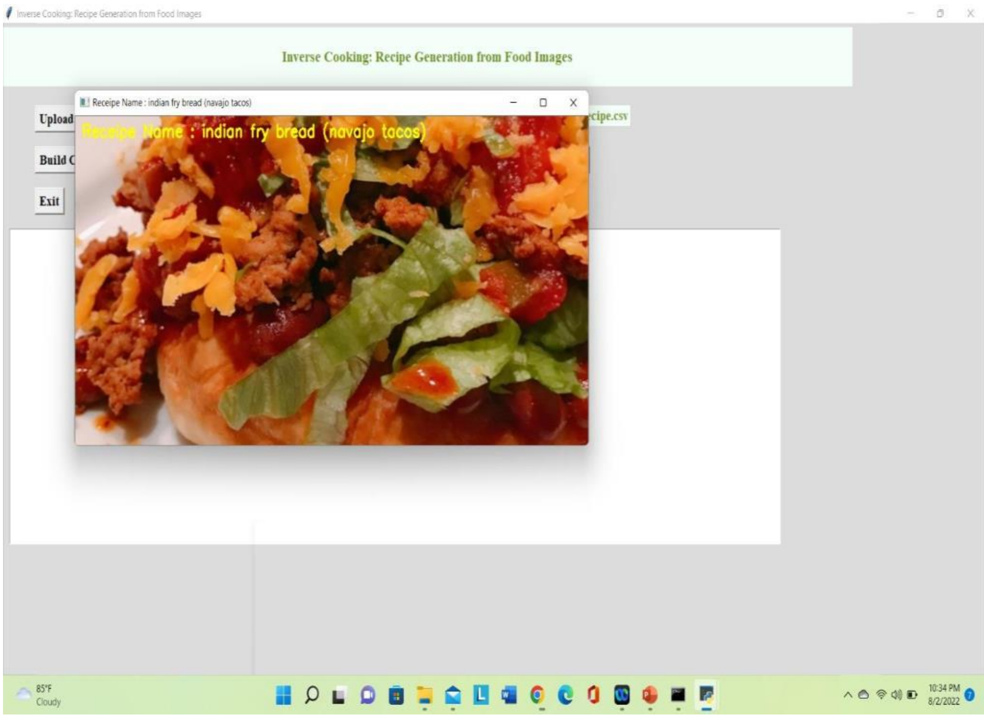

Fig: Output

In above screen uploaded image recipe identified as 'indian fry bread(novojo tocos)' and nowclose above image to get below details.

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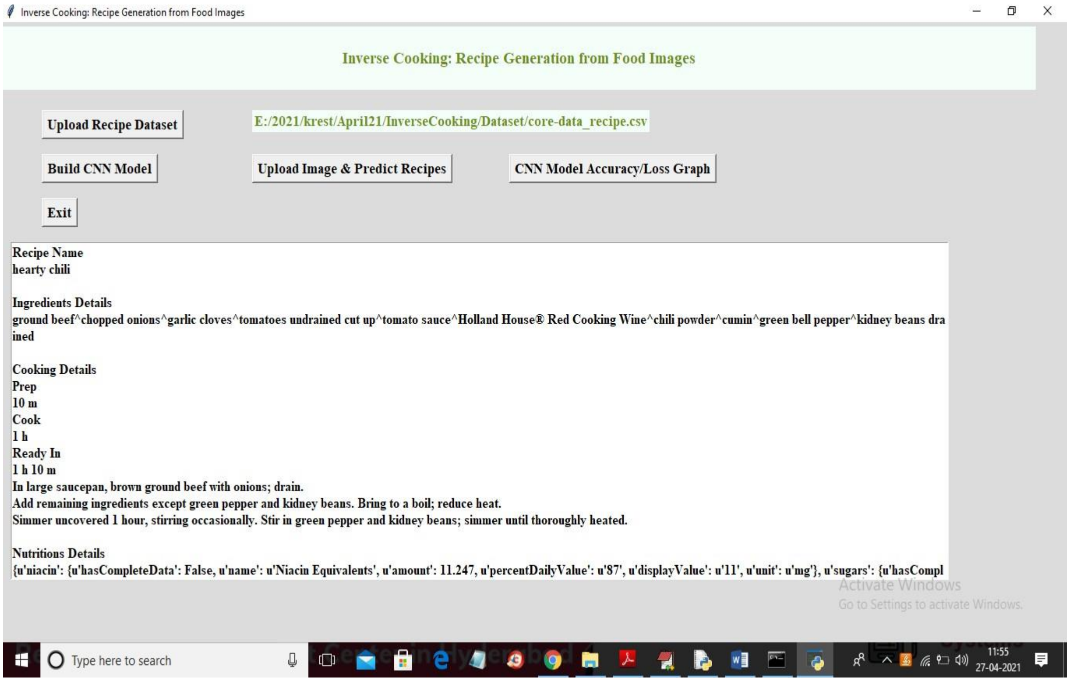

Fig: Nutrition Details

In above screen we can see recipe name, ingredients details, cooking and nutrition details andsimilarly you can upload any image and get recipe.

Now click on 'CNN Model Accuracy/Loss Graph' button to get CNN graph

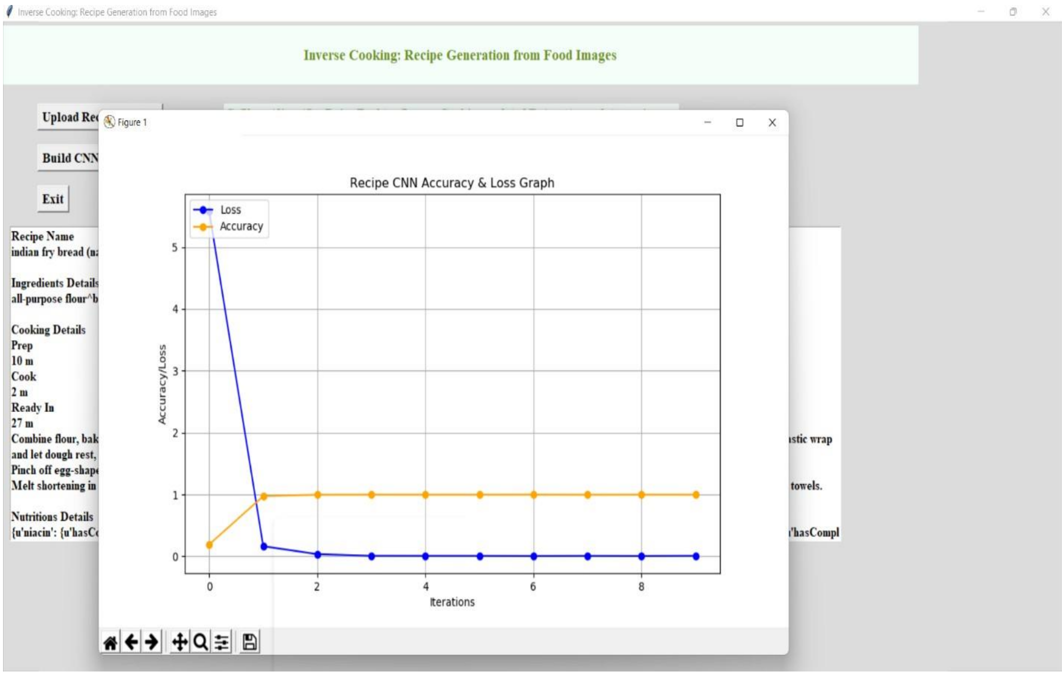

Fig: Accuracy Graph

In above graph x-axis represents epochs and y-axis represents accuracy/loss value and blue line represents loss and orange line represents accuracy and in above graph with each increasing epoch accuracy got increase to 1 (100%) and loss decrease to 0. Any CNN model whose accuracy is highand loss is less will be consider as efficient model.

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V. CONCLUSION

The proposed model can be significantly useful for information retrieval system and it can also be effectively utilized in automatic recipe recommendations. This system an image-to-recipe generation system, which takes a food image and produces a recipe consisting of a title, ingredients and sequence of cooking instructions. We first predicted sets of ingredients from food images, showingthat modeling dependencies matters. Then, we explored instruction generation conditioned on images and inferred ingredients, highlighting the importance of reasoning about both modalities at the same time. Finally, user study results confirm the difficulty of the task, and demonstrate the superiority of our system against state of- the-art image-to-recipe retrieval approaches.

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