STREET FOOD RECOGNITION USING DEEP LEARNING

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APPROVAL

This Project titled "Street Food Detection of Bangladesh Using Deep Learning", submitted by Oyshi Tabassum Aditi, Beauty Banu, and Mehnaz Rashid Mim to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 4th December 2021.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Tarek Habib, Assistant Professor, and Department of CSE, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Street food demand is increasing day by day in Bangladesh. It has yummy tastes, easily accessibility, low price, easily made, easy to available, attraction to the foods, and above all, needs of the street people. There are many different classes of people from many different areas, especially the middle class, poor and the lower-class people come in Dhaka in search job for better earning. And their earning is so low that's why they can buy this type of street food because of low price. Mainly most of the young people eating foods at the street and it is a fashion nowadays. This study has been detected of these street foods can help people detect them. To conduct this study, we used Deep Learning process to build our system of recognition various street cuisine. Deep learning is a strong technology that has been used in a variety of fields to automate fundamental procedures and improve the outcomes of these operations. A total of 3023 images with 14 items of street foods were used to detect. We conduct this captured image and gained our expected feature by using image classification. For image classification of street foods, we used TensorFlow algorithm. We also used Convolutional Neural Network (CNN) for architecture and feature extraction of our Model. The Convolutional Neural Network (CNN) achieved the accuracy of 97.72% , which is good and also giving us inspiration for our next research. Deep learning is being utilized on the field and in the marketplace to boost yield and ensure the quality of street food reaching consumers in the area of street food detection. In this thesis, we planned to create a simple CNN that can recognize street food in images. This system would help the human to reduce the time and effort needed for detecting of street foods at street. We used sequential model to build our system. Deep Learning (DL) has several applications due to its ability to learn robust representations from images. Convolutional Neural Networks (CNN) is the main DL architecture for image classification.

Keyword: Convolutional Neural Network (CNN), Deep Learning (DL), Image segmentation, Feature extraction, Street food detection.

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NOMENCLATURE

ANN	Artificial Neural Networks
CNN	Convolutional Neural Networks
CSV	Comma Separated Values
DL	Deep Learning
FNN	Feedforward Neural Network
FAO	Food and Agriculture Organization
HACCP	Hazard Analysis Critical Control Point
IDE	Integrated Development Environment
RNN	Recurrent Neural Networks
UFP	Ultra-Fine Particles
VOC	Volatile Organic Compound

CHAPTER 1

Introduction

In the previous three and a half decades, street food vending and consumption have increased dramatically. The ready-to-eat or ready-to-drink food or beverage offered on the street or in comparable locations, and street food is prepared by vendors and handlers in public places, or by hawkers or stationery on the go, from a site with or without an interior area to serve clients. International organizations recognize the nutritional, economic, social, and cultural relevance of street food, but they also recognize the serious safety, nutritional, and management concerns it raises [1]. The best street food cities were listed in Figure 1, according to the Street Food City Index 2019 [2].

Figure 1: The best cities for street food in 2019

Street foods are becoming more enticing to food enthusiasts in Bangladesh because of the expansion of information technology and media. Due to the increase of income of city slickers, they spend their vacations getting out of their claustrophobic homes and eating street cuisine in parks and on the streets. Nowadays it is becoming a trend to the people to have various kind of foods. In short food division plays an important role in the economy of Bangladesh. Most of the young people like students and lower classes peoples are growing their interest to eat street food. Street food vendors, who are largely from Bangladesh's rural districts, are the second most frequent informal sector job in metropolitan areas such as Dhaka after rickshaw-pulling. Around 3,000 street sellers offer street food to a million people in Dhaka metropolis [3]. Figure 2 displayed the topmost street foods in Bangladesh.

Figure 2: Street foods in Bangladesh

In most of the cases mobile and hard-working employees, such as rickshaw pullers and construction workers, rely on cheap food and energy-dense snacks to get by during long days on the job [4]. According to a survey conducted by the Food and Agriculture Organization, almost 2.5 billion people eat street food on a regular basis. The key reasons for this are their inexpensive pricing, accessibility, availability, as well as their diversity for a huge number of people.

The rise of a cosmopolitan population from across the country has coincided with the proliferation of street food [5]. Food sellers are generally seen in crowded shopping malls, trading centers, office buildings, railway stations, and bus terminals. Many people are forced to migrate to cities due to a lack of possibilities in rural areas. The majority of the sellers were from rural areas [6] A street vendor is a person who sells things to the general public without having a permanent built-up building but with a temporary static structure. Street foods provides work for many people who would otherwise be unable to find work in the skilled, formal economy. Street Food handlers oversee delivering ready-to-eat meals to a wide range of Bangladeshi residents and visitors [7]

Distinct stakeholders view and perceive street cuisine from various angles. Street cuisine has long been seen as an important component of urban food production. A large portion of the population relies on street food to meet their nutritional needs. Food offered on the streets is cheap and easy to come by. Consumers who do not have enough time to prepare their own meals or who prefer to eat at restaurants with more expensive cuisine and demanding service [8].

It has long been popular among the lower and moderate-income levels, particularly in third world and developing-country cities It is a better option than bringing meals to or near high-traffic locations like schools, parks, playgrounds, marketplaces, roadways, high rises, and tourist destinations [9], [10].

Street food has three distinct characteristics:

- Inexpensive
- Convenient
- Easy to locate in cities, and
- Served in vans or kiosks that can be found on busy commercial streets or at festivals [11].

Food quality control must be precise and efficient in order to fulfill society's rising expectations and standards for food, and it has thus become a time-consuming and labor-intensive task. We also keep track of your daily meals so that we can keep track of what we eat and introduce it to others. Image recognition of food items might be a suitable method to tackle this challenge in food identification. Recently, deep learning has been applied in picture identification [12].

Deep learning is a strong technology that has been used in a variety of areas to automate fundamental procedures and improve the outcomes of these operations [13]. Deep learning has offered its powerful automation and compute capability to large-scale farming in a variety of ways, inclusive of food detection systems have been utilized on the field for analysis and prediction. Deep learning has been applied in the creation for some data-intensive parts. These systems incorporate features such as field data gathering, data analysis, monitoring, prediction, detection and among others. Deep learning is being used to check and detect street food, with the goal of providing reliable information on the quality of detection to consumers. In this thesis, we have used a basic CNN to detect street foods in images [14].

Food recognition using deep learning of convolutional neural networks is a unique and promising application. We created a convolutional neural network that can particularly recognize Bangladeshi famed street cuisines [15]. The convolutional neural network (CNN), which is regarded the most common architecture of deep learning and has been widely employed for the identification and analysis of food, has recently emerged as a successful and potentially useful tool for feature extraction. The structure of CNN, as well as a method of feature extraction based on a sequential CNN model, are discussed in this thesis Moreover, the model architecture and overall performance of CNN are compared to other existing approaches, and future developments in using CNN for food identification and analysis were discussed [16].

In this thesis, deep learning-based expert system is suggested that analyzed a taken image from a mobile or portable device and decided which foods were present. We applied CNN to the detection of street food images and evaluated its performance. It was a multilayer neural network with neurons that take input from tiny areas of the previous layer [17]. We picked 14 delicacies snacks for our experiment from a variety of local street foods, including Shingara, Beguni, Alur chop, Luchi with Chap, Chotpoti, Pakora, Peyaju, Mughlai, Muri, Kola Vorta, Hawai Mithai, Jilapi, Fuchka, Doi Fuchka. We use segmentation to extract anticipated features from the obtained images after preprocessing [18].

This thesis's material was structured as follows: The similarity works were examined in chapter 2, along with background research. The system architecture, data collection, results, features, and potential models are addressed in Chapter 3. The experimental assessments are provided in Chapter 4. The result analysis is detailed in Chapter 5. At last, future studies and a description of the conclusion are given in Chapter 6.

The literature has identified vending techniques and facilities used for dispensing street foods as key factors to cross contamination of street foods [19]. The rise of a cosmopolitan population from all across the country has coincided with the proliferation of street food. Street food vendors are responsible for delivering ready-to-eat meals to a diverse group of locals as well as visitors to Bangladesh [20].

Furthermore, street-level imagery has proven to be useful when combined with other data sources such as social media, as well as for developing new geospatial data and improving current datasets [21]. Street food does not yet have a well-developed regulatory framework in smart cities and smart grids [22].

1.1 Aims and Objectives

The main objective of this research is to introduce various kinds of delicious street foods to the world. In this dissertation, a system was developed that can identify specific street foods in Bangladesh. A convolutional neural network (CNN) was used to solve this problem. For this purpose, around 3023 images are used for the training of the network and around 80% images were used for the training and 20% of those were used for testing of the network.

The reason we picked this strategy is that color is a prominent distinguishing feature of different types of Bangladeshi street foods, and color may be utilized as a categorization criterion.

This thesis intended to identify a means to save time and effort in the street food sorting process, as well as to aid in the inspection and selection of street foods to some extent.

1.2 Limitations of this work

There were only a few limits to this work. They are:

- ❖ The computer was given the data, and then it analyzed. The data cannot be detected by the computer on its own.
- ❖ The examination and photographing of street foods took a significant amount of time and effort.
- ❖ This model necessitated the use of a high-end computer configuration, which is not always available.

To a significant way, the inferences drawn from the customer's basic analysis of the street cuisines might really reveal the quality of the meal, which implies that the seller must ensure that the foods they sell seem appealing to increase sales.

CHAPTER 2

Literature Review

Vending on the street can be viewed as a source of a diverse selection of meals that are nutritionally valuable to certain groups of people. The types of street cuisine available vary widely per country. In addition, meals such as fried pork, fish, and ready-to-eat items based on maize meal are cooked and offered [23] .

In most countries, including Bangladesh, street cuisines have become a typical occurrence. People residing in Bangladesh rely heavily on street food to meet their dietary demands. Street foods are especially appealing in industrialized countries because they are quite tough to cook at home. In this paper, we can discover the elements that encourage food lovers to enjoy street cuisine in Bangladesh. Street food vendors contribute to the economy by creating self-employment and job opportunities for others [24].

Street food is eaten as meals, beverages, and snacks in various countries, and it represents local culinary culture in terms of ingredients, preparation, sales strategies, and ingestion ways. Food and beverages prepared on the street are typically offered in aluminum cans, nylon bags, and newspapers. To assist local governments, the Food and Agriculture Organization (FAO) issued a detailed report on the quality and safety of street food. FAO intervened because many street vendors operate in filthy, unsafe circumstances and lack basic understanding of food hygiene and sanitation, and it was established that they are eager to learn [25].

Along the value stream, it provides ready-made meals at affordable prices and jobs to teeming rural and urban populations. Street food vending tackles key social and economic challenges in developing nations. The purpose of this review research, which is a synthesis of literature studies on risk factors in the developing-country street food industry and in order to ensure safe food practices, safety remedies provide a worldwide benchmark for action. Implementation of safety practices that are implemented throughout the whole street food supply chain, excellent farming methods, as well as hazard analysis and critical control point strategy, as well as proper hygiene procedures by farmers, vendors, and customers, would considerably reduce the risks connected with street food consumption. Above all, Buliyaminu Adegbemiro Alimi recommends that all stakeholders collaborate to improve and effectively execute public health policies in order to promote safe practices and a safer and healthier society. [26].

The risk factors, habits, and knowledge linked to food safety and hygiene were investigated by the food sellers in Uganda's Kampala, Jinja, and Masaka regions. Between August 2008 and May 2009, 225 street food sellers were inspected. In the interviews and focus group discussions, a systematic questionnaire and checklist were employed. Women made up 87.6% of street sellers, and they had a low level of education. Masaka sellers (68.6%) stated that there were no cleanliness laws controlling Hygiene criteria were enforced by local government onsite administration in Kampala (75.9%) and Jinja (65.3%), respectively, in the street food selling sector. Vendors used a variety of vending structures, and the premises were filthy. Vendors requested that the vending locations be improved structurally and that additional hygienic amenities be provided. Street food sellers are aware of hygiene norms, yet they do not follow them. Participants in the focus group discussed the importance of re-emphasizing personal cleanliness and education. Food contamination must be reduced by education and the provision of hygienic facilities at vending places, according to Charles Muyanja, Leontina Nayiga, Namugumya Brenda, and George Nasinyama [27].

In many developing nations, including Ghana, roadside meals have become a key source of prepared meals for most households and people. The knowledge of street food sellers in Ghana's Ejisu-Juaben Municipality on food safety and food handling procedures is investigated in this study. 340 street food vendors participated in the survey (with a 100% response rate). The data was collected using a structured questionnaire and an observational checklist, and then analyzed using STATA version 12. According to the findings, 98.8% of the food sellers had a strong understanding of food safety and handling. The most effective strategy to promote understanding of food safety and improve food-handling standards, according to the study, is to teach food sellers. According to Raymond Addo-Tham, Emmanuel Appiah-Brempong, Hasehni Vampere, Emmanuel Acquah-Gyan, and Adjei Gyimah Akwasi, the larger proportion of female street food vendors in this study illustrates women's societal involvement in food production and distribution in Ghana. Municipal assemblies should collaborate with other organizations to enhance, maintain, and arrange regular training programs for new and existing food sellers, according to the survey, retraining trainers to provide them with the essential knowledge and abilities to properly deliver food vendor training programs. [28].

Ekanem et al. [29] designed largely to promote public awareness of the public health dangers and socioeconomic challenges that the African street food business faces. The study underlined the necessity for African countries to work together to address these concerns and encourage the long-term growth of the street food economy to increase street food consumer and vendor education on basic food safety issues, as well as develop their own street food codes of practice using the Hazard Analysis Critical Control Point (HACCP) approach. Consumers were advised to create groups in order to exercise their rights and have their voices heard on issues that affected them because of their overall weakness on an individual basis.

Food offered in a public setting, such as from a street vendor, or ready-to-eat food, drink, or drinks sold on the street, in a market, fair, park, or other public site. Street foods are an essential part of the diet for millions of low- and middle-income individuals who live in cities on a regular basis. Researchers, humanitarian organizations, and consumer groups are becoming aware of the socioeconomic significance of street food, as well as the risks associated with it. Urbanization and population expansion have encouraged the growth of street food as an illegal business in a number of countries in recent years. As a result, the seminar's purpose was to assess the available information on factors impacting street food consumption, such as microbiological load, sanitary practices, street food safety, and related risk factors. Finally, Sualeh et al. [30] proposed that research be conducted in Ethiopia on street food consumption, notably local 'Jebena-buna,' and the health concerns associated with it.

The research's primary goal was to evaluate a sample of street food sellers' food hygiene methods and attitudes in Dlangezwa et al. [31] in South Africa. Purposive sampling and qualitative research were used in this study. Data was acquired in this article by interview questionnaires and an observation schedule, as well as through face-to-face conversations. The data was analyzed using Microsoft Excel to create graphs and tables based on the replies of the different participants. Few of the vendors in this survey agreed that it was critical to keep food at the right temperature to avoid rotting, and some even said that incorrect food storage may be harmful to one's health. According to Joanne Mjoka and Prof. Mosa Selepe, this necessitates immediate street vendor training in cleanliness and food safety, as well as local government cooperation.

The amount to which foods are processed and by whom varies; some street food sellers also provide an outlet for meals processed by others in the informal sector, as well as small- and large-scale food processing companies in several nations [32].

In Dhaka, Bangladesh's capital, selling meals on the street is a common occurrence. Street food vendors provide daily meals to a huge number of city people from various walks of life, including students, tourists, rickshaw drivers, cart pullers, and other professions. Street foods provides chances for resource-poor populations in urban and rural contexts, not only as a source of employment but also as a reliable source of low-cost nutrition [33].

In Bangladesh, both fast food and street food have grown at risky speed. Street foods are goods that are ready to eat when traveling or walking and include more items such as Shingara, Fushka, and chotpoti; breakfast items such as puri, peyaju, and mughlay etc [34].

Food vendors earn more money than other types of vendors. According to a press release. The average daily income of a street food vendor is roughly SL Rs 1,250, with an average daily profit of SL Rs 575. On average, the bulk of street food sellers operate for 25 days every month. This translates to a monthly profit of SL Rs 14,375 and on average, SL Rs 31,250 a month is earned. The national monthly family income, for example, is SL Rs 13,036 in rural Sri Lanka, compared to SL Rs 23,436 in urban Sri Lanka. This demonstrates that, even though they face the same as with other street sellers, they face similar issues, such as a lack of security and institutional facilities, street food vendors make a significant contribution to the country's economy. The city of Colombo has sought to create a role model for food sellers on the street. The municipality has developed a group of 35 food sellers known as the Galle Face Green Food Vendors, according to Mafasinghe et al. [35], 9 food inspectors for the Colombo Municipal

Council. The municipality offers clean carts that are kept in a clean environment. The public health department acknowledged this group's efforts as an outstanding initiative.

While street food was originally largely associated with the cuisines of developing countries, its popularity in the developed world, particularly in Bangladesh, has grown significantly in recent years [36]. Many tourism sites are putting forward effort to determine basic demands and comprehend why tourists are drawn to street meals. By utilizing local resources, contributing to local economies, and supporting a sustainable tourism system, street foods integrate the authentic culture of the local people with traditional values [37].

Another factor that is frequently overlooked in developing countries is that food carts on streets are exposed to the environment, with no safeguards in place to protect food from contamination by humans or flies, and food is frequently kept at high ambient temperatures that encourage bacterial growth [38].

Lower wages, migrating to cities, suburbanization population development in towns, and the high cost of cheap, delicious, and nutritious meals served near workplaces all contribute to the high cost of affordable, tasty, and nutritious meals, and long commuting lengths between work and home are just a few of the variables that have aided the growth of street food in Africa. [39].

In Malaysia, street food vending generates a multibillion-dollar industry that employs sellers and food handlers directly [40]. It's unlikely that the popularity of street food sellers would wane [41].

Street food safety is governed by national legislation. Operators in the EU, on the other hand, used HACCP concepts or at the very least good hygiene standards in accordance with national competent authorities, as required by the food hygiene rule [42].

If people had persisted in the hunter-gatherer modes of existence, which provided at least street food safety if not food security, the decision on what to eat and where to eat would have been considerably easier [43].

Cart food can be delicious, and it allows residents and city workers to sample culinary diversity and culture from around the world. Street food sellers in North America generally use propane gas and/or charcoal to prepare or process food within their vehicles. Furthermore, liquid fossil fuels (diesel, gasoline, and liquefied petroleum gas) are frequently used to create energy for the street food.PM2.5, CO, ultra-fine particles (UFPs), and volatile organic compounds (VOCs) are anticipated to be primary sources of emissions from such fuels [44].

According to a report published by the Food and Agriculture Organization (FAO) in 2014, 204 million individuals in Sub-Saharan Africa are chronically malnourished and rely primarily on street food [45].

Most Southeast Asian countries, including Vietnam, are known for their huge range of inexpensive street cuisine. The demand for street foods has expanded in Asia as a result of increasing urbanization and the social and structural changes that have resulted. In 2011, Vietnam adopted precise measures to control the safety of street foods for the first time in their new Food Safety Law. The ordinance includes detailed instructions on how to run a street food business [46]. Figure 1 depicted the applications of deep learning.

2.1. Deep Learning via Different Networks

Deep Learning (DL) enables researchers and developers to solve challenges involving real-world information computationally (Figure 3). Convolutional neural networks (CNN), recurrent neural networks (RNN), artificial neural networks (ANN), and other types of deep learning neural networks are transforming how we communicate and interact. The deep learning revolution is based on these distinct types of neural networks.

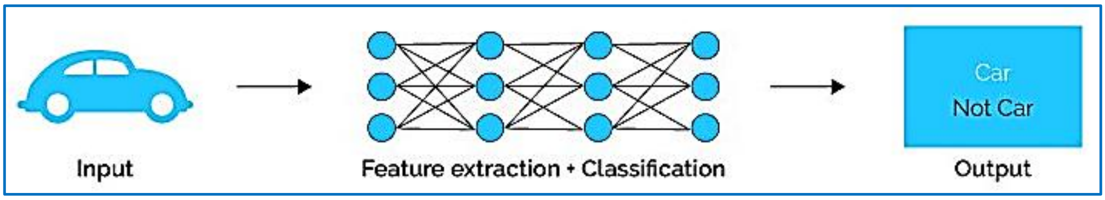

Figure 3: Neural networks of deep learning

Despite the fact that there are hundreds of different deep learning models, they can be categorized into primary types (Figure 4). The important forms of deep learning networks that are accessible are explored further below:

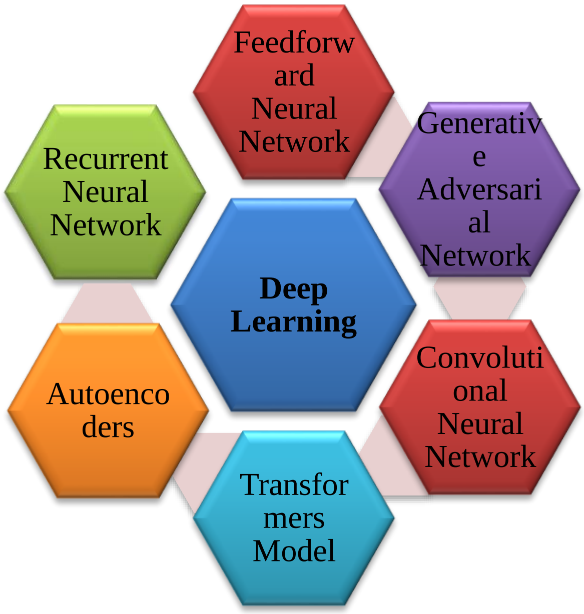

Figure 4. Significant models of Deep Learning

2.1.1. Feedforward Neural Network (FNN)

The most basic neural network is the feedforward neural network, which controls flow from the input layer to the output layer (Figure 5). There is just one layer, or one hidden layer, in these networks. Because data only goes one direction, there is no backpropagation mechanism in this network. The total of the weights in the input is sent to the input layer of this network. A facial identification system based on computer vision uses FNN.

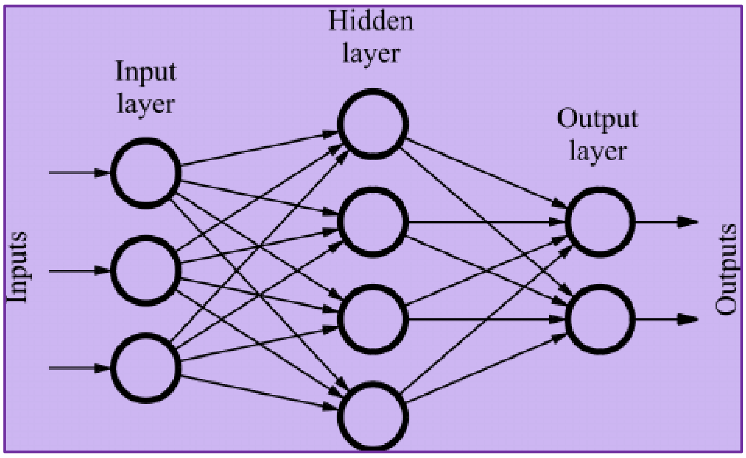

Figure 5: Feed Forward Neural Network

2.1.2. Recurrent Neural Network (RNN)

On the concealed state, RNN has a recurrent connection. The output of one neuron is given back as an input to the same node in an RNN. This strategy aids the network's output prediction. The parameters of RNNs are shared between time steps. This type of network is good for keeping a tiny state of memory, which is important for chatbot development. Figure 6 depicted the recommended recurrent neural network architecture [47].

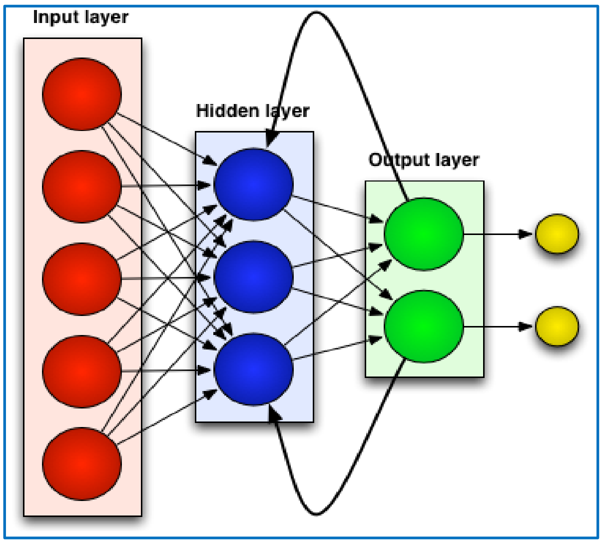

Figure 6: Recurrent Neural Network

2.1.3. Convolutional Neural Networks (CNN)

Convolutional Neural Networks are the most used deep learning architecture for image categorization (CNN). The use of CNN for street food recognition has been significantly improved by using new models or pre-trained networks for transfer learning, resulting in good results. One of the most extensively used machine learning (ML) algorithms is deep learning (DL). The capacity to automatically learn patterns inherent in pictures and a high level of abstraction are two basic aspects of DL. For image processing, the Convolutional Neural Network (CNN) is the most often used DL architecture. According to their findings, DL-based algorithms, notably CNNs, are gaining popularity (in 2017) because they automatically learn picture characteristics and minimize image identification error [48]

The Convolutional Neural Network (CNN) has acquired a lot of traction as a pattern recognition approach, especially in food recognition investigations. This is because, even with modest CNN configurations, the recognition capability is remarkable [49]. Visual imagery is analyzed using a convolutional neural network as depicted in Figure 7.

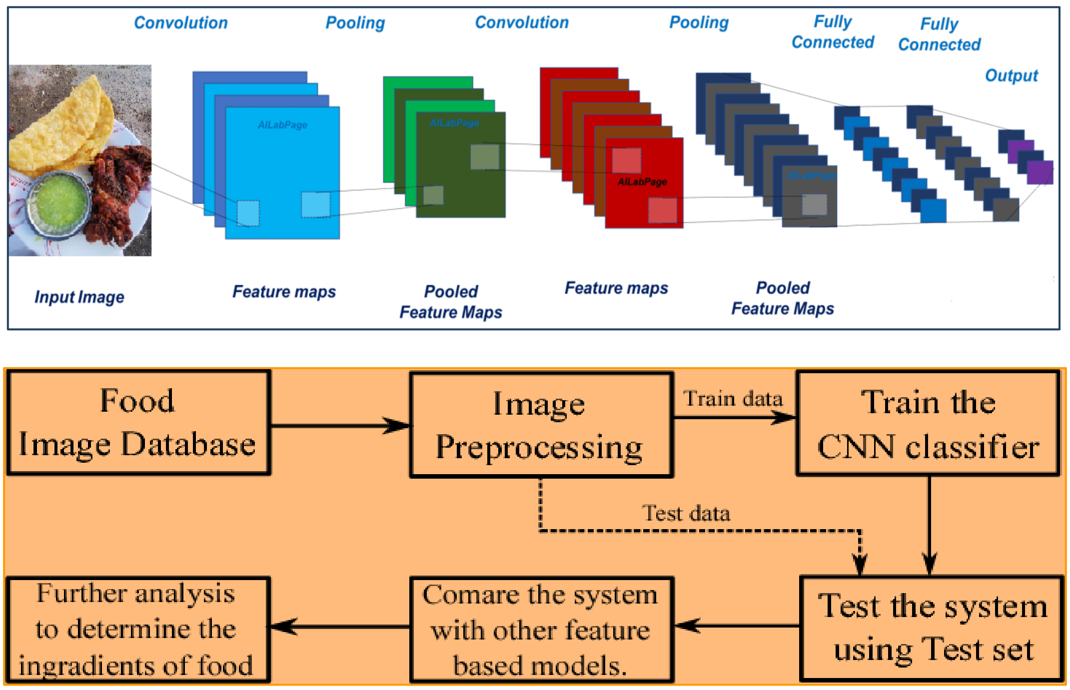

Figure 7: A convolutional neural network used to analyze visual imagery and the paradigm for recognizing food things from photographs

The Convolutional Neural Network (CNN) is the next step in the evolution of the Artificial Neural Network (ANN). They are, nevertheless, not dissimilar to a regular neural network. Like standard neural networks, they have inputs, weights, and biases. The inputs and weights, as well as their sums, are subjected to operations such as dot-product and non-linearity. In CNN when the cat sees basic shapes, simple cells (in the visual cortex) activate, while it perceives shifted or rotated versions of the original forms, complex cells (in the visual cortex) use the combined information from S cells to activate [50]

The fundamental issue with CNNs is that they require big datasets to avoid overfitting, in addition CNN needs a lot of computer capacity to train them [48]. It is an alternation of the typical deep neural network (DNN) that removes and combines local characteristics from a two-dimensional input using a specific network design consisting of alternating convolutional and pooling layers [51].

Convolutional neural networks (CNN) have gained a lot of traction as a way to classify and categorize images. CNN is superior to traditional hand-crafted feature extraction-based approaches because it can adaptively learn the best features from images. Researchers must collect a large-scale dataset in order to deploy CNN for image classification. Because of its great accuracy, CNNs are employed for picture categorization and identification [52].

The CNN uses a hierarchical architecture that builds a network in the shape of a funnel and then outputs a fully-connected layer where all the neurons are connected to one another and the output is processed. CNN's key benefit over its predecessors is that it automatically finds essential elements without the need for human intervention. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself [52].

In most of the investigated studies, convolutional neural networks (CNNs) and its derivative algorithms have been identified as key methods for automatically learning deep characteristics of input digital information for later classification or regression tasks. Deep learning is currently being used in the food industry to analyze RGB and spectrum photos of food. However, because comprehending and implementing deep learning is a difficult task for researchers and workers in the food business, researchers are working on it. Food images are one of the most important sources of information on the properties of food [53].

Keras and TensorFlow are two of the most popular CNN architectures for image processing. Where tensorflow provide both higher and lower and it is open source.The models that have been consulted are written in Python and employ TensorFlow libraries. But Keras is not an open source and it provides high end API only. Even for voice recognition apple Siri uses tensorflow. Tensorflow provide both high and low API. But Keras provide only high end API. By using Tensorflow we can create CNN model [54].

On November 9th, 2015, Google released TensorFlow, a framework. TensorFlow gets its name from the operations that artificial neural networks execute on multidimensional data arrays, such as adding and multiplication. These arrays are referred to as tensors, which is a small change. It is a good idea to look at what we will be working with before we start loading data. Convolutional Neural Networks (CNN) in TensorFlow.

Our thesis mainly describes the information on street cuisine in developing nations that is currently accessible. The street food industry contributes significantly to urban economies. The majority of street food businesses are run by a single person or a family. According to a research conducted in Pune, India, the majority of vendors owned only one kiosk/stall or cart (only 12% owned two or fewer than two), and the majority received help from family members (45%), paid workers (8%), or both (19%).Similarly, 90 percent of vendors in Jamaica were sole proprietorships, with the other 10% being joint partnerships. It's crucial to remember that the street food sector is both a retail and a production activity: while the selling of street meals is the most apparent aspect of the business, most street foods have been processed in some way, with much of it taking place off-street [55]. The majority of street food vendors selling both raw and cooked foods are unregulated. They operate carelessly, with no oversight of what they do [56].

For object detection, CNNs have been the most widely used deep learning method. As a consequence, all of the deep learning models discussed in this paper employ the CNN.

Before image classification, it is necessary to do region extraction on numerous items in order to detect various things. The sliding window approach was the most frequent method of regional extraction prior to deep learning [57].

The transition module is a unique regularization approach for CNNs that collects filters at several scales and compresses them using global average pooling to make moving between convolutional and FC layers easier. With 91.9 percent accuracy rates, the transition module was able to successfully adapt to a small data set [58].

The adoption of artificial neural networks could be a game-changer. Because of their superior performance, Image categorization has piqued the interest of convolutional neural networks (CNNs). Furthermore, the use of graphics processing units (GPUs) allows CNNs to have more complex architectures capable of learning a huge number of characteristics from datasets [59].

We describe our method for automatically classifying street food images in this paper, and show how it works with big image sets. The approach can also be used to classify single particles in other situations. It consists of five steps: (1) image capture, (2) curation of a training image set, (3) image preprocessing, (4) CNN training, and (5) CNN application to classify a broader street food image set [60].

Cross-entropy loss functions were employed initially to create an end-to-end annotation structure for training, and subsequently Wasserstein generative adversarial networks were used for multilevel data augmentation. In the realm of image labeling, the deep neural network model has achieved significant progress [61].

2D CNN alone cannot extract discriminating spectral features efficiently, while 3D CNN is computationally complex. The goal is to combine the capabilities of 3D and 2D CNN in order to extract crucial spectral–spatial properties of HSI for classification. A comparison of numerous state-of-the-art CNN-based HSIC frameworks described in recent literature is also carried out [62]. The upgraded version of CNN is used to apply time–frequency pictures of angular domain signals [63]. Deep CNN architectures have been created for a variety of segmentation applications in robotics, manufacturing, the Internet of Things, and medical image analysis [64]. The property of CNN multi-view spectrogram is employed to improve detection performance [65].

CHAPTER 3

Research Methodology

Several tools and libraries were required at various phases of our system's construction. At the core of the process, we collected our data manually. Around 3023 images we used where we trained 2419 data and tested 604 data to implement our system.

We used Convolutional Neural Network (CNN) algorithm to design our model. We used Sequential based model of Convolutional Neural Network to build our system. For architecture review of our model, there were significant tools we used TensorFlow employed at the system's core. As we used manual data for our research, for the purpose of image Display we used PhotoViewer. We also used Virtual Studio Code (VS Code) to display our Figures and used Jupyter Notebook to write our code. The step-by-step procedure was represented in Figure 8.

3.1 Software Applications

First and foremost, we chose to design the system in Python since it is one of the simplest programming languages and works well with TensorFlow. In addition, there are several Python packages that might be useful in achieving our goal.

3.2 Tensor Flow

Tensorflow is a Google-developed open-source software framework for numerical computing that is now widely utilized by many big businesses. Tensorflow gives us a way to communicate your machine learning algorithms, as well as an application for performing them [66].

3.3 Sequential Model

For the recognition of street food, we used a CNN-based sequential model. In Keras, the simplest technique to build a model is sequential. It enables us to layer-by-layer construct a model. To add layers to our model, we use the 'add()' function. Conv2D layers make up our initial two layers. These are convolution layers that will deal with our 2-dimensional matrices as input images [68].

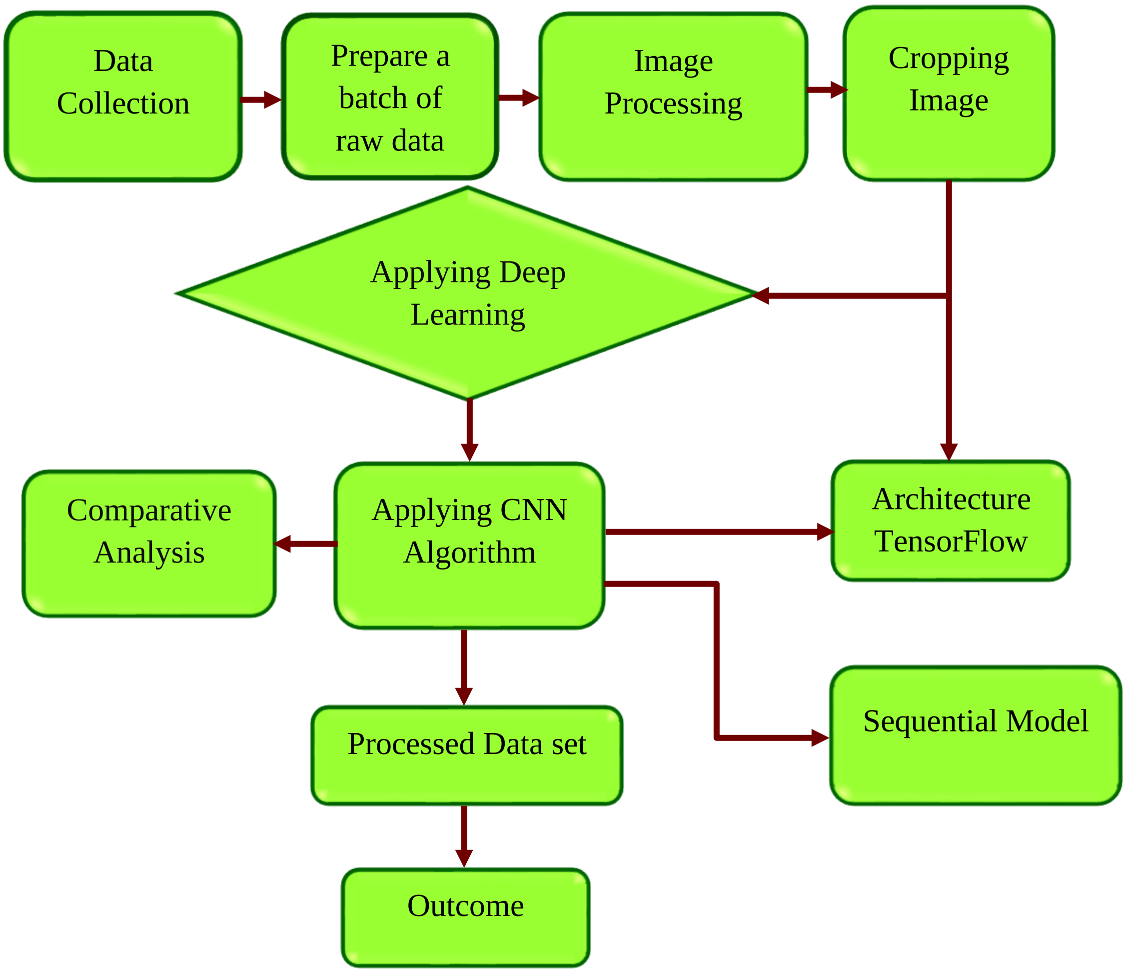

Figure 8: Flow chart depicting a step-by-step procedure for working approaches

3.5 Visual Studio Code

Using the Microsoft Python plugin in Visual Studio Code to work with Python is simple, enjoyable, and productive. The addon transforms VS Code into a fantastic Python editor that runs on every operating system and supports a wide range of Python interpreters. Visual Studio is perhaps the most serious IDE on the planet, as well as the best Microsoft product ever created. It does all of the tasks for which it was designed. It features the best syntax support of any IDE, making your coding experience considerably smoother and quicker [69].

3.6 Jupytar Notebook

The original web application for producing and sharing computational documents is Jupyter Notebook. It provides a straightforward, simplified, and document-focused environment [70].

3.7 Python Virtual Environment

A virtual environment is a tool that creates separated python virtual environments for distinct projects to keep their dependencies separate. Most Python programmers utilize this as one of their most significant tools. Python packages for various projects are managed using the Python virtual environment. You can avoid installing Python packages globally, which could disrupt system tools or other projects, by using a virtual environment [71].

CHAPTER 4

Experimental Process

4.1. Data Collection

Data collection is the process of acquiring and evaluating information on variables of interest in a systematic manner that allows researchers to answer research questions, test hypotheses, and assess outcomes.

The purpose of creating a dataset of Bangladeshi street food photos must consider the three factors below. To begin, the dataset must include as many photographs of Bengali street cuisine as feasible, with each item being represented by as many images as possible. Furthermore, the resolution of the dish photographs varies according on the phone camera used, as a result, a dataset with photographs of varying resolutions may be used to create a more realistic portrayal of street food. We began by testing with a dataset of Bengali street food created by Janaki Prasad Koirala et al., which was freely available [1].

We created our own dedicated dataset from scratch by using the CNN as our primary source. The dataset consists of 14 items-based images. Almost all possible variations within a category are acknowledged. We sought a dataset that was acceptable for use in the state-of-the-art CNN framework for street food detection because our goal was to employ it. These were the most important specifications for the training dataset.

We all are collected data to 14 items. These are: Item 1=Alur Chop, Item 2=Beguni, Item 3=Chaap with Luchi, Item 4=Chotpoti, Item 5 = Doi Fuchka, Item 6 = Fushka, Item 7 = Hawai Mithai, Item 8 = Jilipi, Item 9 = Kola Vorta, Item 10 = Mughlai, Item 11 = Muri, Item 12 = Pakora, Item 13 = Peyaju, Item 14 = Shingara. And given this all 14 items before processing all data are given below in Figure 9:

Figure 9: Alur Chop, Beguni, Chaap with Luchi, Chotpoti, Doi Fuchka, Fuchka, Hawai Mithai, Jilipi, Kola Vorta, MughlaiMuri, Pakora, Peyaju, and Shingara before image processing

4.2. Data Processing

Data processing is the process of simply transforming raw data into understandable format. We splitted the dataset into two groups for training and testing, in 3023 images and here 2419 for training and 604 images for testing.

The manipulation of data by a computer is known as data processing. Data processing includes the use of computers to execute defined operations on data. It is the collection and manipulation of items of data to produce meaningful information.

Data is a collection of values for one or more variables. A variable is a sample characteristic with distinct values for different subjects. Numeric, counting, and category values are all possible.

When observed that when we are collecting data then all the size of the images and resolution are so high. Therefore, we processed these all data.

	A	B	C	D
1	fileName	index	width	height
2				
3	1-Jan	1	768	1024
4				
5	2-Jan	1	768	1024
6				
7	3-Jan	1	768	1024
8				
9	4-Jan	1	768	1024
10				
11	5-Jan	1	768	1024
12				
13	6-Jan	1	768	1024
14				
15	7-Jan	1	768	1024
16				
17	8-Jan	1	768	1024
18				
19	9-Jan	1	768	1024
20				
21	10-Jan	1	768	1024
22				
23	11-Jan	1	768	1024

Figure 10: Csv dataset with images index no. and height, width

Here, Figure 10 displayed our all item resizing images after processing with height, width. Now, all processing images were given below in Figure 11:

Figure 11: Alur Chop, Beguni, Chaap with Luchi, Chotpoti, Doi Fuchka, Fuchka, Hawai Mithai, Jilipi, Kola Vorta, MughlaiMuri, Pakora, Peyaju, and Shingara before image processing

4.3. Color

The potential of RGB cameras to extract and measure the color of delicious cuisins was assessed using the image analysis technique. We used direct RGB color of out images because it gives beeter output of our model.

4.4. Experimental Setup

We used our own pc to complete all setup and config also data processing and train the model. Deep learning allows a user to submit an enormous quantity of data to a computer algorithm, which then analyzes and makes data-driven suggestions and judgments based only on the supplied data. We activated virtual environment because before we can start installing or using packages in our virtual environment we will need to activate it. Activating a virtual environment will put the virtual environment-specific python and pip executables into your shell's path (Figure 12). A virtual environment is a tool that creates separated python virtual environments for distinct projects to keep their dependencies separate.

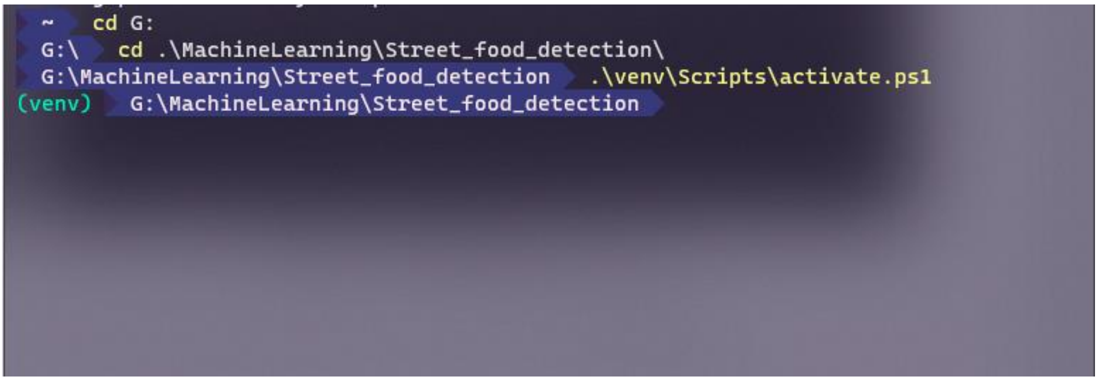

Figure 12: Activating virtual environment

In Figure 13, we created a folder which name is machine learning, but it is not an algorithm because it is just a folder name. And we created this virtual environment for Street Food Detection.

Then we opened a Jupyter Notebook (Figure 14). Because a Jupyter Notebook is an easy-to-use, interactive data science environment that may be used as a presentation or teaching tool as well as an integrated development environment (IDE).

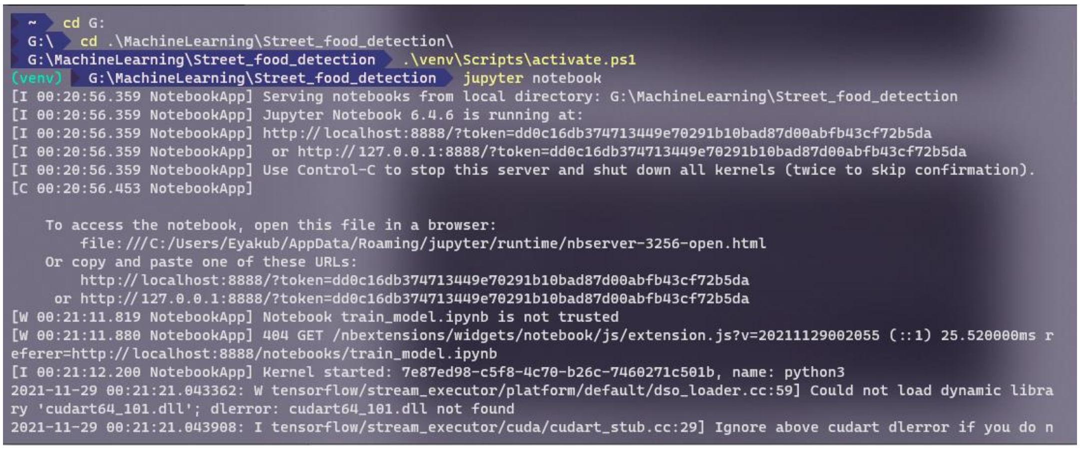

Figure 13: Opening Jupyter Notebook

Then created all interface for street food detection on this Juypter Notebook. The Jupyter Notebook is a free open-source web application that allows data scientists to create and share documents that include live code, equations, computational output, visualizations, and other multimedia features, as well as explanatory text.

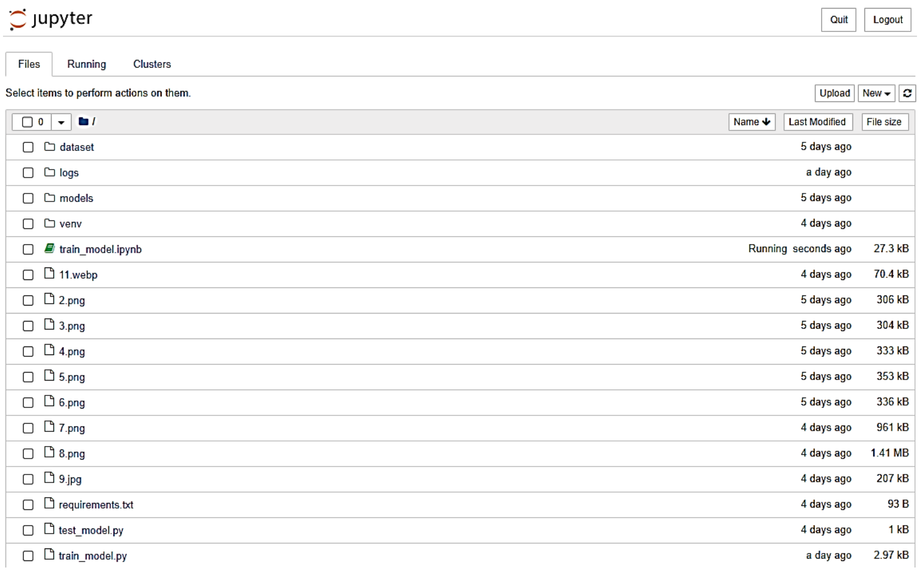

Figure 14: Jupyter Notebook Interface

Then, we installed all libraries like OpenCV, NumPy, tqdm, Python-CSV, SKlearn, TensorFlow==2.3.0, puppeteer, and MLX tend. Then imported this all required libraries. Figure 15 was showed all interface for street food detection.

```python
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Flatten, Dense, Dropout,BatchNormalization,Conv2D,MaxPool2D,MaxPooling2D
import datetime
import tensorflow as tf
```

Figure 15: Imported required library

Here, the above figure showed all imported library. Importing a function into a Python module gives it access to code from another module. The import statement is the most common method of triggering the import machinery, but it is by no means the only one.

Image processing, computer vision, and machine learning are all supported by OpenCV, a big open-source library. OpenCV supports Python, C++, Java, and a variety of additional programming languages. It can distinguish objects, people, and even human handwriting in images and videos. It was used to process images in this thesis.

NumPy is a Python module that allows you to interact with arrays. And tqdm is a Python library that wraps around any repeatable and produces a smart progress bar. And CSV (Comma Separated Values) is a straightforward file format for storing tabular data in spreadsheets and databases. Scikit-learn is without a doubt the most useful machine learning package in Python. Tensorflow==2.3.0 is the latest version of tensorflow which used for our model creation. And Puppeteer is a promise-based library, therefore it makes asynchronous calls. It is a node library that allows you to control headless Chrome through the Find vulnerabilities Protocol. Keras is a free open-source Python framework for constructing and evaluating deep learning models that is both powerful and simple to use. It uses tensorflow backend. And Mlxtend (machine learning extensions) is a Python package with a variety of useful tools for data science jobs.

CHAPTER 5

Result and Discussions

Our acceptable data set was created by collecting 3023 data. Finally, we trained the model in the full 14 items with 3023 following the test phase. People may identify different types of food using the provided factors and then pick the meal that best suits their needs. For evaluation we used Convolutional Neural Network algorithm. We divided the complete dataset into two portions:

1. Using the training portion to train the model and the testing portion to test the model
2. Using 3023 images for training and 604 images for tasting data, according to this procedure.

We used a CNN method based on deep learning for our process data set, with the number of 10 features. For the extraction of features we used CNN algorithm.

```
Epoch 1/10
  1/242 [..............................] - ETA: 0s - loss: 1.0692 - accuracy: 0.0000e+00WARNING:tensorflow:From g:\machinelearn
ing\street_food_detection\venv\lib\site-packages\tensorflow\python\ops\summary_ops_v2.py:1277: stop (from tensorflow.python.eag
er.profiler) is deprecated and will be removed after 2020-07-01.
Instructions for updating:
use `tf.profiler.experimental.stop` instead.
242/242 [==============================] - 468s 2s/step - loss: 0.4608 - accuracy: 0.4907 - val_loss: 2.2042 - val_accuracy: 0.
0198
Epoch 2/10
242/242 [==============================] - 494s 2s/step - loss: 0.1129 - accuracy: 0.8130 - val_loss: 1.1805 - val_accuracy: 0.
1455
Epoch 3/10
242/242 [==============================] - 500s 2s/step - loss: 0.0771 - accuracy: 0.8825 - val_loss: 0.6737 - val_accuracy: 0.
4430
Epoch 4/10
242/242 [==============================] - 512s 2s/step - loss: 0.0605 - accuracy: 0.9173 - val_loss: 1.0588 - val_accuracy: 0.
2876
Epoch 5/10
242/242 [==============================] - 509s 2s/step - loss: 0.0488 - accuracy: 0.9400 - val_loss: 0.6002 - val_accuracy: 0.
5322
Epoch 6/10
242/242 [==============================] - 482s 2s/step - loss: 0.0392 - accuracy: 0.9545 - val_loss: 0.4302 - val_accuracy: 0.
6942
Epoch 7/10
242/242 [==============================] - 483s 2s/step - loss: 0.0284 - accuracy: 0.9739 - val_loss: 0.2532 - val_accuracy: 0.
8215
Epoch 8/10
242/242 [==============================] - 501s 2s/step - loss: 0.0301 - accuracy: 0.9669 - val_loss: 0.1334 - val_accuracy: 0.
9091
Epoch 9/10
242/242 [==============================] - 492s 2s/step - loss: 0.0257 - accuracy: 0.9760 - val_loss: 0.1015 - val_accuracy: 0.
9041
Epoch 10/10
242/242 [==============================] - 500s 2s/step - loss: 0.0255 - accuracy: 0.9772 - val_loss: 0.0749 - val_accuracy: 0.
9372
WARNING:tensorflow:From g:\machinelearning\street_food_detection\venv\lib\site-packages\tensorflow\python\training\tracking\tra
cking.py:111: Model.state_updates (from tensorflow.python.keras.engine.training) is deprecated and will be removed in a future
version.
Instructions for updating:
This property should not be used in TensorFlow 2.0, as updates are applied automatically.
WARNING:tensorflow:From g:\machinelearning\street_food_detection\venv\lib\site-packages\tensorflow\python\training\tracking\tra
cking.py:111: Layer.updates (from tensorflow.python.keras.engine.base_layer) is deprecated and will be removed in a future vers
ion.
```

Figure 16: Epoch form model

The epoch for data were seen in Figure 16. The amount of passes the Deep learning algorithm has made through the whole training dataset is referred to as an epoch. The whole train-set processing by the learning algorithm is referred to as an epoch in Deep Learning. Each epoch consisted of 242 data points.

From Figure 16, we can see in 2nd step that validation loss starts increasing and validation accuracy starts decreasing. This means model was cramming values not learning. And it has no 1st step because all steps had previous data but for 1st step had no previous data. The same things happened for 3rd, 4th and 5th step. But, for 6th step validation loss starts decreasing and validation accuracy starts increasing. This was also fine as that means model built is learning and working fine. The same things happened for 7th, 8th, 9th and 10th step.

And we know that validation loss and validation accuracy both starts increasing. This could be case of overfitting or diverse probability values in cases where softmax iwa being used in input layer.

A strategy for measuring the performance of a Deep learning algorithm is the train-test split. It can be used for any supervised learning technique and can be utilized for classification or regression tasks.

```
In [3]: data = np.load('dataset/train_test_set/compressed_processed_train_test_set_01.npz')
        x_train = data['x_train']
        x_test = data['x_test']
        y_train = data['y_train']
        y_test = data['y_test']

In [4]: x_train

Out[4]: array([[[[0.54901963, 0.4627451 , 0.36862746],
                 [0.5568628 , 0.47843137, 0.38431373],
                 [0.5568628 , 0.47843137, 0.38431373],
                 ...,
                 [0.50980395, 0.42745098, 0.36078432],
                 [0.50980395, 0.42745098, 0.36078432],
```

Figure 17: Splitting train / test data

The results of the tests were shown in Figure 17. We used it because we should separate our data into train, validation, and test splits to prevent our model from over fitting and to accurately evaluate our model. When we put input here and train our model then it gives a tested data.

Plotting figure used for image processing. The data that we collected were so big in size. So, we processed this all data and resized this also. Figure 18 depicted the heights and widths of some of the data.

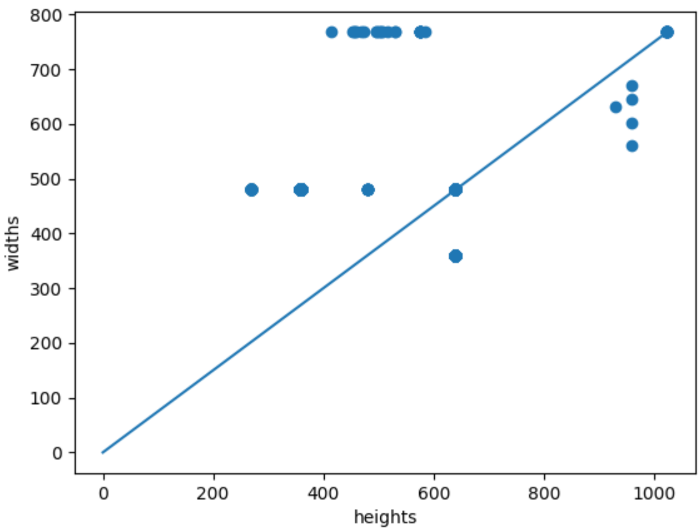

Figure 18: Figure plotted according to height, width

```
model = Sequential()
model.add(Conv2D(16,(3,3),activation='relu',input_shape=x_train[0].shape))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.2))
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.3))
model.add(Conv2D(64,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.4))
model.add(Conv2D(128,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.5))
model.add(Conv2D(256,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.6))
model.add(Conv2D(512,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(128,activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(y_train.shape[1],activation='sigmoid'))

```

Figure 19: Sequential Model. (Training model)

We used Sequential Model to build our system (Figure 19). The simplest method to create a model with TensorFlow and Keras is to use a sequential model. It allows you to layer-by-layer construct a model. To add layers to our model, we utilize the 'add()' method. Conv2D layers make up our initial two layers. These are convolution layers that will deal with our 2-dimensional matrices as input images. In a decision-making process, sequential modeling demonstrates the capacity to effectively deal with certain complexity. When the complexity of decision-making difficulties necessitates the examination of a feasible route to optimal solutions. We offer the concept of a sequence of comparisons in this thesis, as well as a decision-making model. Initially, additive values are collected using a sequential model, and various features are investigated [72].

The rectified linear activation function (Relu) for short was a piecewise linear function that if the input is positive, outputs the input directly which used for created our training model (Figure 20). And we used it because it is simple, fast, and empirically it seems to work well. The vanishing gradient problem is solved by the rectified linear activation function (Relu), which allows models to train quicker and performs better [73].

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 448, 456, 16)	448
batch_normalization (BatchNo	(None, 448, 456, 16)	64
max_pooling2d (MaxPooling2D)	(None, 224, 228, 16)	0
dropout (Dropout)	(None, 224, 228, 16)	0
conv2d_1 (Conv2D)	(None, 222, 226, 32)	4640
batch_normalization_1 (Batch	(None, 222, 226, 32)	128
max_pooling2d_1 (MaxPooling2	(None, 111, 113, 32)	0
dropout_1 (Dropout)	(None, 111, 113, 32)	0
conv2d_2 (Conv2D)	(None, 109, 111, 64)	18496
batch_normalization_2 (Batch	(None, 109, 111, 64)	256
max_pooling2d_2 (MaxPooling2	(None, 54, 55, 64)	0
dropout_2 (Dropout)	(None, 54, 55, 64)	0
conv2d_3 (Conv2D)	(None, 52, 53, 128)	73856
batch_normalization_3 (Batch	(None, 52, 53, 128)	512
max_pooling2d_3 (MaxPooling2	(None, 26, 26, 128)	0
dropout_3 (Dropout)	(None, 26, 26, 128)	0
conv2d_4 (Conv2D)	(None, 24, 24, 256)	295168
batch_normalization_4 (Batch	(None, 24, 24, 256)	1024
max_pooling2d_4 (MaxPooling2	(None, 12, 12, 256)	0
dropout_4 (Dropout)	(None, 12, 12, 256)	0
conv2d_5 (Conv2D)	(None, 10, 10, 512)	1180160
batch_normalization_5 (Batch	(None, 10, 10, 512)	2048
max_pooling2d_5 (MaxPooling2	(None, 5, 5, 512)	0
dropout_5 (Dropout)	(None, 5, 5, 512)	0
flatten (Flatten)	(None, 12800)	0
dense (Dense)	(None, 128)	1638528
batch_normalization_6 (Batch	(None, 128)	512
dropout_6 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 14)	1806

Total params: 3,217,646
Trainable params: 3,215,374
Non-trainable params: 2,272

Figure 20: Model Summary

Figure 20 displayed the total 3,217,646 params. And params means the number of parameters that are trained for each layer. Consequently, we used total 3,217,646 parameters in our model. In this model it has 3,215,374 trainable params and 2,272 are non-trainable params.

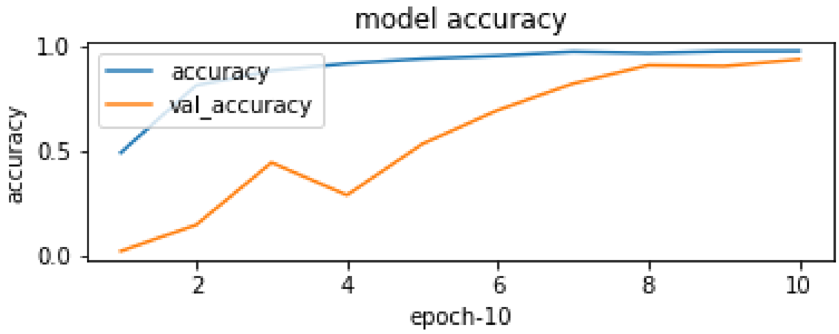

Figure 21: Graph of accuracy and performance evaluation

For the training model, we chose 10 epoch and the greatest 1.0 accuracy, as shown in Figure 21. Here, blue color bar showed the accuracy and yellow color bar was shown the validation accuracy. For epoch 2 accuracy was around 0.1, for epoch 4 accuracy was around 0.4. We observed for 4 epoch accuracy decreased than 3 epochs. But accuracy was increasing continuously for next other epochs like epoch 6, epoch 8 and epoch 10.

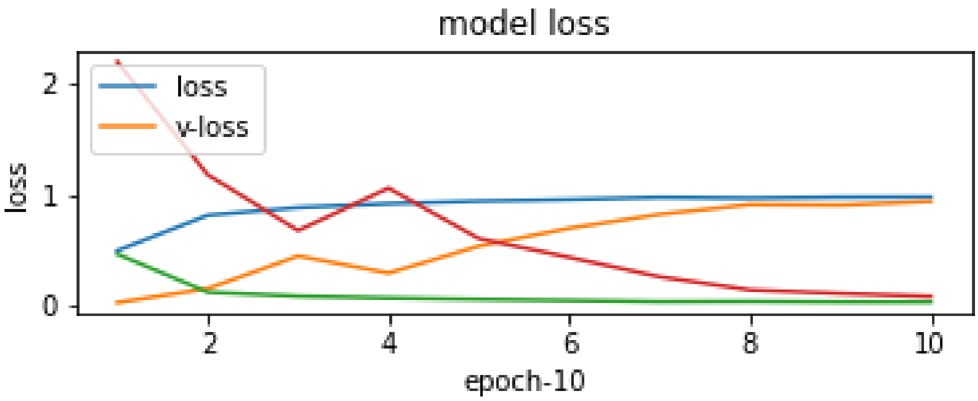

Figure 22: Graph of loss and performance evaluation

Figure 22 depicted the validation loss over a period of ten epochs. The loss was represented by a blue color bar, whereas the validation loss was shown by a yellow color bar. For epoch 2 loss was around 0.5, for epoch 4 loss was around 1.0. But loss was same for next other epochs like epoch 6, epoch 8 and epoch 10.

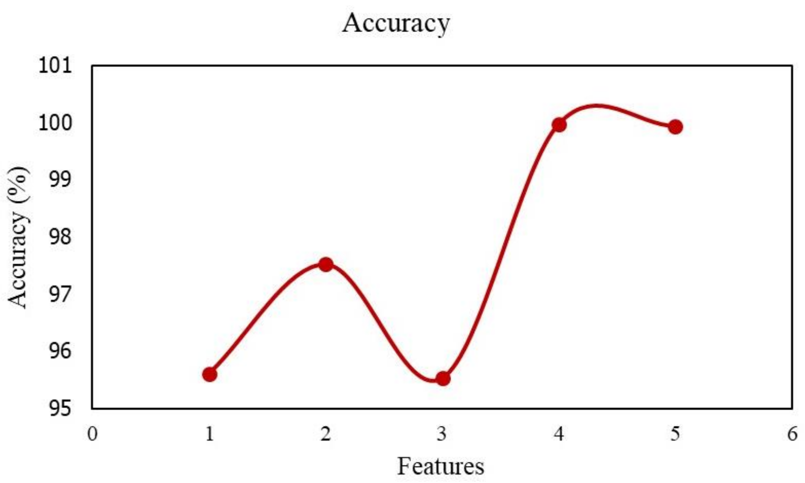

Figure 23: Variation of the accuracy values.

This approach may be used to calculate the accuracy % of various Bangladeshi street dishes.

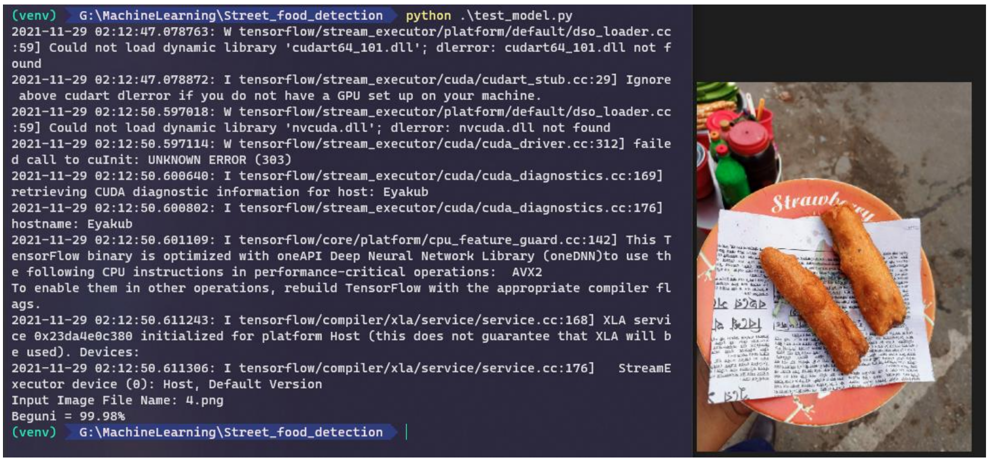

Figure 24: 99.98% accuracy for Beguni

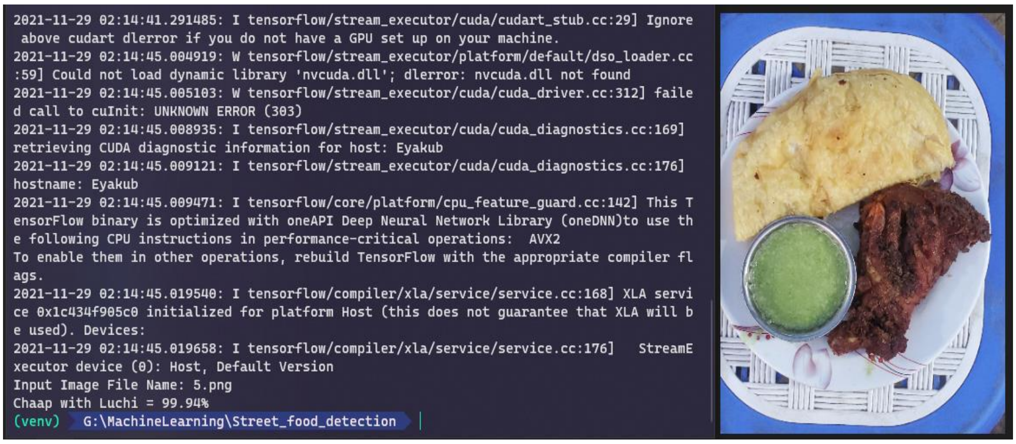

Figure 25: 99.94% accuracy for Chaap with Luchi

Figures 23 and 24 illustrated the accuracy of Beguni, Chaap, and Luchi, with Beguni having 99.98 percent accuracy and Chaap having 99.94 percent accuracy with Luchi.In, this same way, we checked the accuracy for other 12 items as well. Although we got 97.7% accuracy in average. When compared to prior research studies employing deep learning to recognize food, street food, fruits, or other related objects, we achieved a high level of accuracy.

CHAPTER 6

Comparative Analysis of our Result to other Results

We have compared our work to other works in the field. We discovered the merits of our suggested food identification system after assessing existing study efforts. We discovered that there was a lot of effort had done for forecasting after reading many research papers. Nonetheless, we have struggled to compare our work against that of others based on a set of criteria. The table of given below shows a comparative analysis to other relevant works with ours.

In this thesis, they have several significant limitations. The system had to be able to recognize defective or spoiled food, which was a huge issue. M. Darwish analyses that it was unattainable due to a lack of datasets generated specifically for this purpose. However, because the photos are displayed as image histograms, differences in the color pigment of good and poor cuisine might allow rotten cuisine to go undetected. Although this appears to be a temporary solution, it is not as complex as a system trained on photos of genuine damaged foods. In addition, they were unable to put this idea to the test. [74]. On the other side Janaki Prasad Koirala utilized the subcategories of the ImageNet Challenge dataset as categories for their dataset in their study, which included food, drinks, and fruits. The label's image count with the fewest samples. They employed pre-trained weights from the ImageNet dataset as their primary dataset, which was a subset of ImageNet. They also noticed that their network swiftly converged after roughly 10k iterations as a result of this. Despite the fact that they did not gather their data, they recognized that it would not be a useful application until they had legitimate data. One of the restrictions was that the thesis was a one-person effort. They had to study and comprehend the influence because they were limited by a small dataset, they couldn't develop an optimal model that performed well with a small number of data sets using the Faster RCNN framework, or even build an ideal model that functioned well with a small number of data sets [75].

Furthermore, Alfiero et al. [76] noted that, while the DEA approach to food service management is an effective system, it had certain constraints, such as sample size and the number of factors evaluated, that limited the findings of the research and discussion.

With a greater number of Food Truckers, a more in-depth analysis of the phenomenon could be conducted, as well as the incorporation of elements that took into account the diverse service delivery conditions (Table 1).

Table 1: The comparison of our work to other works produced the following results.

Different works	Object (s) Dealt with	Sample Size	Technique used	Segmentation Algorithm	Size of Feature Set	Accuracy
Present Work	Street Food (Alur Chop,Begunii,Chaap with Luchi,Chotpoti,Doi Fuchka,Fushka,Hawai Mithai,Jilipi, Kola Vorta,Mughlai, Muri,Pakora,Peyaju,Shingara)	3023 images	Deep Learning	-	10	97.7%
Ciaocca et al. [77]	Food	3616 images	Machine Learning	ground-truth (GT)	-	61.34%
Poulazzadeh e al. [78]	Food(steak and potatoes)	-	Deep Learning	-	-	94.11%
Zhang et al. [79]	18 different categories of fruit	1653 images	Classical Machine Learning	Otsu's Method	79	88.2%
Rocha et al. [80]	Fruits and Vegetables	2633 images	Classical Machine Learning	k-means clustering	-	-
Ringland et al. [81]	Fruit (banana, built, cassava, maize, rice,	48,000 images	Deep Learning	DeepLab	40	83.3%

	and sugarcane)					
Middel et al. [82]	Street Canyons(sky, trees, buildings, impervious surfaces, pervious surfaces, and non-permanent)	257 images	Deep Learning	-	-	95%
Marutha, et al. [83]	Street Food Vendors	312 images	Machine Learning	-	-	91.2%
Jeaheng, et al. [37]	Street Food	417 images	Deep Learning	-	-	63.235%
Sanlier, et al. [84]	Street Food	847 images	Machine Learning	-		-
Nigar et al. [24]	Street Food (25 items)	340 images	Deep Learning	-	-	-

By comparing these articles, we were able to create our own dataset from several Bangladeshi streets. We may conclude from the preceding table that our accuracy (97.7%) is superior to that of others, and that our effort is focused on Bangladesh. We did our best to discover the best accuracy using a variety of deep learning techniques, and we were able to get a satisfying outcome.

For the sake of establishing our entire model, we have a large dataset. We had no data shortages, and this thesis was a collaborative effort. This is an unique street food-related idea for research purposes, and the accuracy of our model was 1.0 in the conclusion. This is a higher level of accuracy than many other articles. We utilized the subcategories of a street food photograph from our dataset collection as categories for our dataset. We tried with a variety of data subsets. Using the CNN as our primary source, we built our own specialized dataset from the ground up. However, the final set of tests were conducted on a dataset, which was separated into two groups for training and testing, with 3023 pictures for training and 604 images for testing. The dataset contains 14 photos based on items. To eliminate sample bias, this number was chosen. Within a category, almost all conceivable variants are accepted. We required a dataset that was acceptable for use in the state-of-the-art CNN framework for street food detection because our goal was to employ it. These were the most important specifications for the training dataset. To demonstrate the findings, a CNN-based model was created that can identify images and distinguish street food. We did collect our data, therefore we knew it would be a viable application because we have legitimate data. However, data might be collected from many street corners in Bangladesh.

We can investigate and comprehend the influence of training samples on the Faster CNN architecture now that we have a larger dataset. We've all gathered data on 14 different street food items and those are Alur Chop, Begunii, Chaap with Luchi, Chotpoti, Doi Fuchka, Fushka, Hawai Mithai, Jilipi, Kola Vorta, Mughlai, Muri, Pakora, Peyaju, Shingara.

When we collected data, the picture sizes and resolutions were all really high. As a result, we must process all of the data. We prepared a csv file including the image index number as well as the height and width. Our whole item resizing photos after processing with height and width are shown in the csv dataset. We conducted the initial setup and configuration data processing, as well as training the model, on our own computer.

We obtained the intended result by utilizing deep learning on our dataset. Deep learning eliminates some of the data pre-processing that machine learning generally entails. These algorithms can ingest and interpret unstructured data such as text and photos, as well as automate feature extraction, which reduces the need for human specialists. The deep learning system then changes and fits itself for accuracy via gradient descent and backpropagation methods, allowing it to generate more precise predictions about a fresh snapshot of street food.

We designed an epoch form model that displays data epoch. An epoch in Deep Learning refers to the learning algorithm's complete processing of a train set. Per epoch, 242 data are trained. The second stage of validation loss begins to increase, while validation accuracy begins to decrease, according to this model. The train-test split is a mechanism for evaluating the success of a Deep learning system that may be used to any supervised learning technique. So that we can determine whether classification or regression activities are required. We have supplied various figures depicting the testing data, an image processing plotting figure, and a training model for the sake of model approach. The impact of training samples in datasets on recognition/prediction quality was investigated. We can see that there are a total of 3,217,646 parameters in the model summary. There are 3,215,374 trainable params and 2,272 non-trainable params in this model. We utilized 10 epoch from the graph of accuracy and performance assessment to reach the greatest accuracy of 1.0. The validation loss is shown in the graph of loss and performance evaluation for 10 epochs. We can independently verify the correctness of each street food item.

We discovered that for the models to perform better on unknown data, they needed a balanced quantity of training samples in the dataset. Finally, the program is capable of accurately predicting street food. This is for the aim of identifying street food that can be used for detecting street food and for commercial purposes for a zone base where which form of street food works best.

CHAPTER 7

Conclusion

This is a research project that will use deep learning, which is a subset of machine learning. We'll be processing a huge number of picture datasets with deep learning.

The primary goal of this thesis was to create a CNN framework that could detect and localize street food products in images. A CNN-based model was created for this purpose and applied in our system. Our original goal was to use a Bangladeshi street food dataset, which was readily available for our research. Instead, we used a subset of our own dataset, which contained roughly 3023 photos of street snacks, to train our model. On this dataset, we continued our investigations. We began the thesis by reviewing current research in Machine Learning, Deep Learning, and/or image processing, particularly as it relates to object detection.

We discovered in the literature that CNN-based algorithms were promising in terms of performance and accuracy in image processing jobs. We began by looking at the connection between the brain and convolutional neural networks. We investigated traditional neural network approaches such as activation functions, loss functions, and so on.

Finally, we spoke about convolutional and deep networks. As previously said, we intended to first detect localization information on photos before recognizing the item. We needed to investigate and comprehend the impact of 3023 data photographs on this framework. We tested with several functions and then measured training loss for each one. For the sake of model approach, we have included numerous figures displaying the testing data, an image processing plotting figure, and a training model. To get the largest accuracy of 1.0, we used 10 epochs from the graph of accuracy and performance assessment.

Our model is functional and recognizes photographs in the dataset. We improve this by using bigger food-image datasets to train the model. Overall, our strategy works for food categories for which we have sufficient samples. In this way, we were able to achieve a portion of our original target. We are more convinced after this experiment that research on automated street food identification is worthwhile. Because of data, we must not compromise the quality of our studies and outcomes. We highly advise any future researchers working on comparable topics to gather data and/or label data using Mechanical Turk. A good set of facts to work with lays the way for a clearer path to the objective.

In the corporate sector, deep learning for street food detection and sorting has a lot of promise. This might be very useful for food identification and allowing merchants to provide high-quality service to their customers. Deep learning can help with basic operations and enhance the quality of street food and services in one of the most underappreciated but significant ways. The system developed in this thesis makes advantage of the visual processing capabilities of convolutional neural networks to help in the detection and prediction of street food. The system, on the other hand, may be improved to do a lot more.

For future work, we can even create systems that can 'generate' new types of cuisine based on food photographs and ingredients. That is, it may be possible to construct an AI chef that augments the street food recipe with new machine-generated dishes. In addition, such an app could be able to provide sanitary services and ensure consumer health safety.

To conclude, street food prediction is an important research area that should be explored further and given more research and development resources because its development and improvement can have a far-reaching impact on both the food industry and the quality of street food served in public spaces.

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