DETECTING MYCOTOXIN – A DATA DRIVEN APPROACH FOR ENSURING FOOD SAFETY

A PROJECT REPORT

Submitted by

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in partial fulfillment for the course

CS19643 – FOUNDATION OF MACHINE LEARNING

For the degreeof

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY , CHENNAI

MAY 2024

RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI

BONAFIDE CERTIFICATE

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Submitted to Project Viva-Voce Examination held on__________________

Internal Examiner **External Examiner**

ABSTRACT

Our project Mycotoxin Detection in Foods for making sure the safety of the food and Reliability addresses a critical concern in the terms of food security and public health. Mycotoxins these are toxic compounds produced by fungi, producing significant risks to human and animal health when present in food which are then in taken by them. Detecting these contaminants plays important role for ensuring the safety and reliability of food supplies. This project employs the principle working of CNN for detecting specific substances mycotoxin patterns in the food item, to identify mycotoxins in food materials swiftly and accurately. By harnessing the power of CNNs, the project aims to provide food safety officers, farmers, and consumers with timely information regarding the presence of mycotoxins in food products,not only the officials but the accessibility is for public too. Through the integration of machine learning techniques, particularly utilizing datasets related to fungal growth, the project enhances the efficiency and accuracy of mycotoxin detection. Machine learning algorithms analyze vast amounts of data to identify patterns associated with fungal contamination, thereby enabling early detection and intervention measures. By including CNNs and other machine learning concepts, this project not only contributes to the advancement of food safety technologies but also empowers stakeholders across the food supply chain to make informed decisions regarding food quality and safety. Ultimately, the implementation of this innovative approach facilitates proactive measures to mitigate the risks posed by mycotoxins, safeguarding public health and enhancing the reliability of the global food system.

ACKNOWLEDGMENT

First, we thank the almighty god for the successful completion of the project. Our sincere thanks to our chairman **Mr. S. Meganathan B.E., F.I.E.,** for his sincere endeavor in educating us in his premier institution. We would like to express our deep gratitude to our beloved Chairperson **Dr. Thangam Meganathan Ph.D.,** for her enthusiastic motivation which inspired us a lot in completing this project and Vice Chairman **Mr. Abhay Shankar Meganathan B.E., M.S.,** for providing us with the requisite infrastructure.

We also express our sincere gratitude to our college Principal, **Dr. S. N. Murugesan M.E., PhD.,** and **Dr. P. KUMAR M.E., PhD, Director computing and information science , and Head Of Department of Computer Science and Engineering** and our project coordinator **Dr.S.Vinoth Kumar** for his encouragement and guiding us throughout the project towards successful completion of this project and to our parents, friends, all faculty members and supporting staffs for their direct and indirect involvement in successful completion of the project for their encouragement and support.

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CHAPTER 1

INTRODUCTION

Ensuring food safety and reliability have become a very important feature in today's globalized food supply chain, where foodborne illnesses and contaminants pose significant risks to public health and economic stability. And after the pandemic hit ,it has become the first priority for the public. Mycotoxins, toxic compounds produced by fungi, represent a pervasive threat to food safety, leading to regulatory concerns and economic losses across agricultural sectors worldwide. In response to this pressing issue, our project aims to develop a comprehensive approach to mycotoxin detection in food materials, machine learning algorithms and concepts.

At the heart of our project lies the imperative to safeguard public health by detecting and mitigating the presence of mycotoxins in food products. These naturally occurring toxins can contaminate a wide range of agricultural commodities, including grains, nuts, and spices, posing serious health risks when consumed in sufficient quantities. By employing CNNs, which are analytical concepts in Machine Learning and are capable of detecting specific biological patterns in the food images, we seek to enhance the efficiency and accuracy of mycotoxin detection in food samples. The utilization of this offers several advantages, including rapid detection times, high sensitivity in detection level thereby facilitating timely interventions to prevent contaminated products from entering the food supply chain.

Furthermore, our project endeavors to empower key stakeholders involved in food safety management, including food safety officers, farmers, and consumers, with the necessary tools and knowledge to identify and address mycotoxin contamination effectively. By providing reliable detection methods and actionable insights, we aim to enhance the capacity of food safety officers to enforce regulatory standards and monitor compliance throughout the food production and distribution process. For farmers, early detection of mycotoxin contamination can enable targeted interventions to mitigate fungal growth and minimize crop losses, like maize thereby safeguarding both agricultural yields and consumer health. Likewise, informed consumers equipped with awareness about mycotoxin risks can make more informed food choices, contributing to overall public health and well-being.

Innovatively, our project integrates machine learning techniques with comprehensive datasets on fungal species and mycotoxin profiles to augment the accuracy and efficiency of mycotoxin detection. By the use of our project the user will be able to enable early detection of fungal growth and timely intervention measures.

In summary, our project represents a multifaceted approach to mycotoxin detection in food materials, with overarching objectives to ensure food safety, empower stakeholders, and harness technological innovations for the betterment of public health and agricultural sustainability. Through collaborative efforts and interdisciplinary expertise, we aspire to make significant strides in safeguarding the integrity and reliability of the global food supply chain, thereby enhancing consumer confidence and well-being.

1.1 PROBLEM STATEMENT

The project aims to enhance food safety and reliability through mycotoxin detection in food materials. By Using CNNs as core concept, the initiative seeks to detect mycotoxins present in food, crucial for ensuring the quality and safety of consumables. Utilizing machine learning algorithms alongside datasets pertaining to fungal growth, the project endeavors to improve the accuracy and efficiency of mycotoxin detection processes. Ultimately, this effort not only empowers food safety officers, farmers, and consumers with crucial information regarding food safety but also contributes to raising awareness about the risks associated with mycotoxin contamination in food products.

1.2 SCOPE OF THE WORK

The scope of the project "Mycotoxin Detection in Food Materials" encompasses several objectives crucial for ensuring food safety and reliability. Primarily, it aims to develop a Convolutional Neural Networks based project of detecting mycotoxins in food, aiding food safety officers, farmers, and consumers in recognizing potential hazards. Along with other machine learning techniques on datasets of fungi enables the detection of fungal growth, further enhancing food safety measures. The project aims to create a comprehensive solution that not only identifies mycotoxins but also mitigates risks associated with fungal contamination, ultimately safeguarding public health and fostering awareness within the food industry.

1.3 AIM AND OBJECTIVES OF THE PROJECT

The aim of the project is to enhance food safety and reliability by developing effective methods for detecting mycotoxins in food materials. This initiative seeks to empower food safety officers, farmers, and consumers with timely information regarding food safety risks. Integrating with other machine learning techniques with datasets on fungal growth enhances the precision and efficiency of mycotoxin detection. Ultimately, the project aims to establish a robust framework for ensuring the safety and integrity of food supplies while raising awareness among stakeholders about the risks associated with mycotoxins.

1.4 EXISTING SYSTEM:

The existing system for mycotoxin detection in food materials is pivotal for ensuring food safety and reliability. It serves as a critical tool for food safety officers, farmers, and consumers alike, empowering them with vital information about the food they handle and consume. At its core, this system utilizes biosensors, sophisticated devices capable of detecting minute quantities of mycotoxins present in food samples. These biosensors offer rapid and accurate detection, enabling timely intervention to prevent potential health hazards associated with mycotoxin contamination. Furthermore, the integration of machine learning algorithms enhances the system's capabilities by leveraging datasets on fungal growth. By analyzing patterns and trends within these datasets, machine learning algorithms caneffectively identify potential sources of contamination and predict future occurrences.

This proactive approach not only aids in early detection but alsoenables stakeholders to implement preventive measures to mitigate risks effectively. Overall, the existing system stands as a robust framework for mycotoxin detection in food materials, providing a comprehensive solution for ensuring food safety and reliability throughout the supply chain. Through the synergy of biosensors and machine learning technologies, it equips stakeholders with the necessary tools to safeguard public health and uphold industry standards.

CHAPTER 2

LITRETURE SURVEY

A literature survey encompassing international conference papers regarding mycotoxin detection in food materials, aimed at ensuring food safety and reliability, along with raising awareness among food safety officers, farmers, and consumers, demonstrates a concerted effort towards addressing a critical aspect of food security. The utilization of biosensors for mycotoxin detection, coupled with machine learning algorithms leveraging datasets of fungal growth, presents a multifaceted approach to mitigate the risks associated with mycotoxin contamination in food.

Firstly, the utilization of biosensors for mycotoxin detection underscores a significant advancement in analytical techniques within the realm of food safety. These biosensors offer rapid, sensitive, and specific detection capabilities, enabling timely interventions to prevent mycotoxin-related health hazards. The integration of biosensors into food safety protocols not only streamlines the detection process but also enhances the overall efficiency of food quality control measures.

The incorporation of machine learning algorithms in conjunction with datasets pertaining to fungal growth represents a paradigm shift in the domain of predictive analytics for food safety. By harnessing the power of artificial intelligence, these algorithms can discern intricate patterns within the data, facilitating early detection of fungal contamination and preemptive measures to mitigate mycotoxin accumulation. The machine learning augments its precision and reliability of mycotoxin detection systems, thereby bolstering the resilience of food supply chains against contamination risks.

However, despite the promising prospects offered by machine learning algorithms in mycotoxin detection, several challenges persist. One of the primary concerns revolves around the standardization and validation of these technologies across diverse food matrices and environmental conditions. Variability in sample composition and matrix complexity necessitates robust validation protocols to ensure the accuracy and reproducibility of detection results. Additionally, the cost implications associated with implementing advanced detection technologies pose a barrier to widespread adoption, particularly in resource-constrained settings.

Furthermore, the efficacy of mycotoxin detection strategies is contingent upon comprehensive risk assessment frameworks that encompass pre-harvest, harvest, and post-harvest stages of food production. Integrating risk assessment models with real-time monitoring systems can enhance the predictive capabilities of detection technologies, enabling stakeholders to proactively mitigate mycotoxin contamination risks. Additionally, fostering interdisciplinary collaborations between food scientists, microbiologists, engineers, and data scientists is imperative to foster innovation and address the complex challenges associated with mycotoxin detection and mitigation.

In conclusion, the literature survey of international conference papers elucidates the multifaceted approach adopted towards mycotoxin detection in food materials, with a focus on ensuring food safety and reliability.

The convergence of biosensors, machine learning algorithms, and risk assessment frameworks heralds a new era in proactive food safety management, empowering stakeholders to safeguard public health and uphold the integrity of global food supply chains. While challenges abound, the collective efforts of researchers, policymakers, and industry stakeholders hold the promise of a safer and more resilient food future.

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CHAPTER 3
SYSTEM DESIGN

3.1 GENERAL

In this section, we would like to show how the general outline of how all the components end up working when organized and arranged together. It is further represented in the form of a flow chart below.

3.1 SYSTEM ARCHITECTURE DIAGRAM

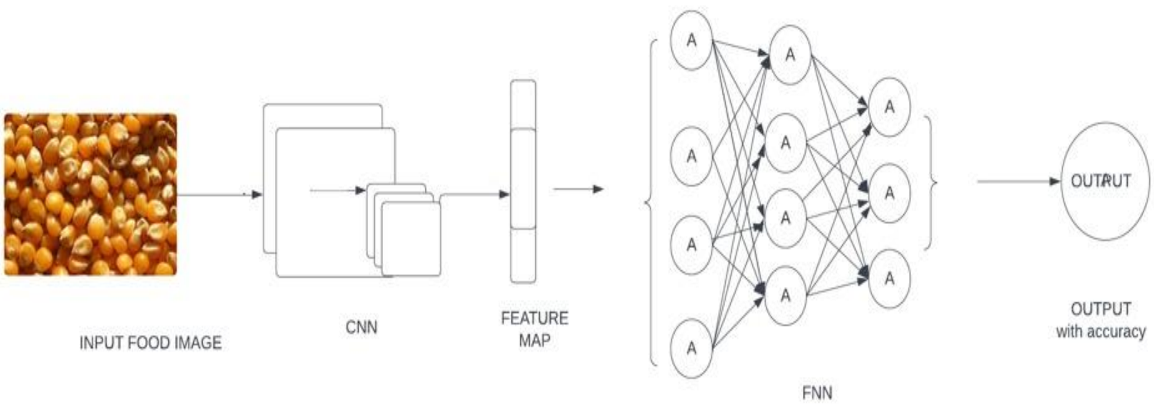
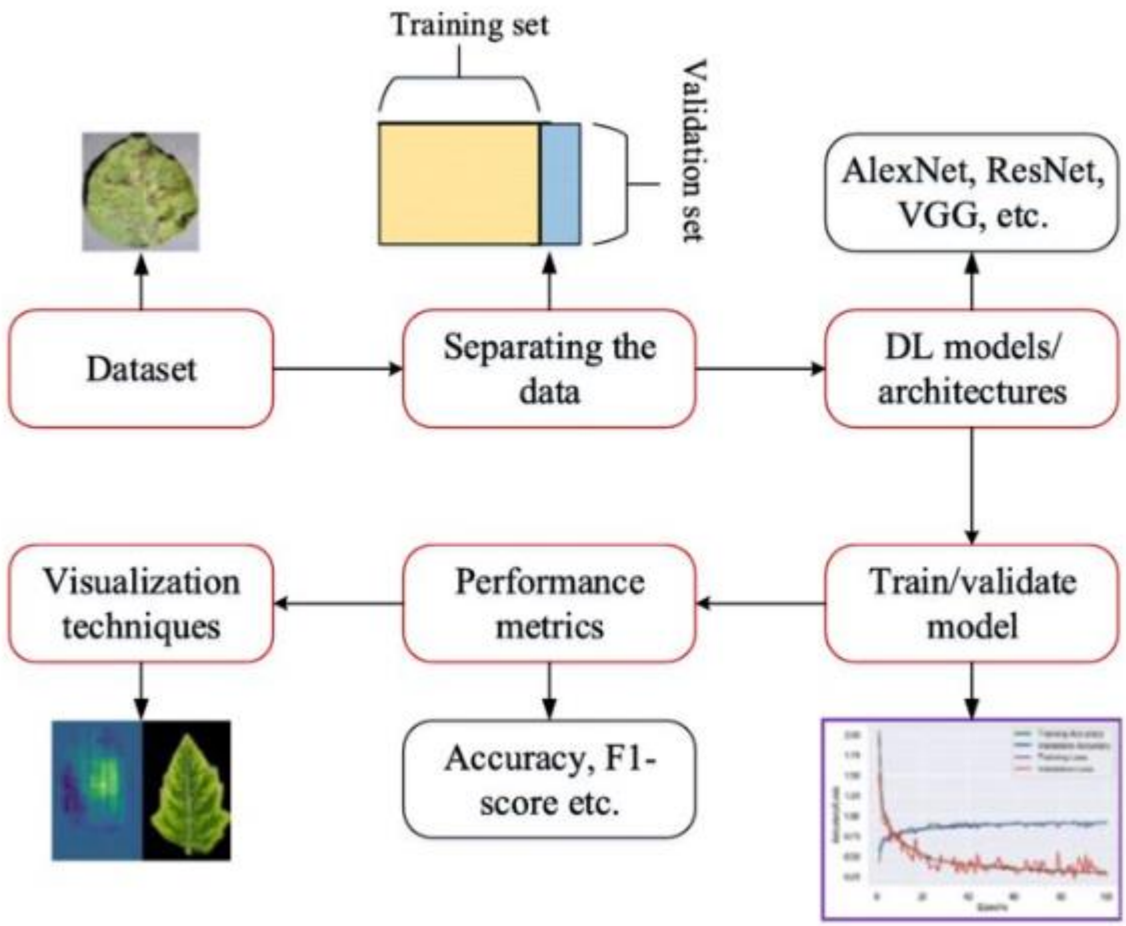


Fig 3.1: System Architecture

3.3 SYSTEM FLOW DIAGRAM:



3.4 SEQUENCE DIAGRAM

A sequence diagram is a type of interaction diagram in the Unified Modelling Language (UML) that illustrates the interactions between objects or components within a system in a chronological order. It provides a dynamic view of the system's behaviour by depicting the sequence of messages exchanged between different entities over time.

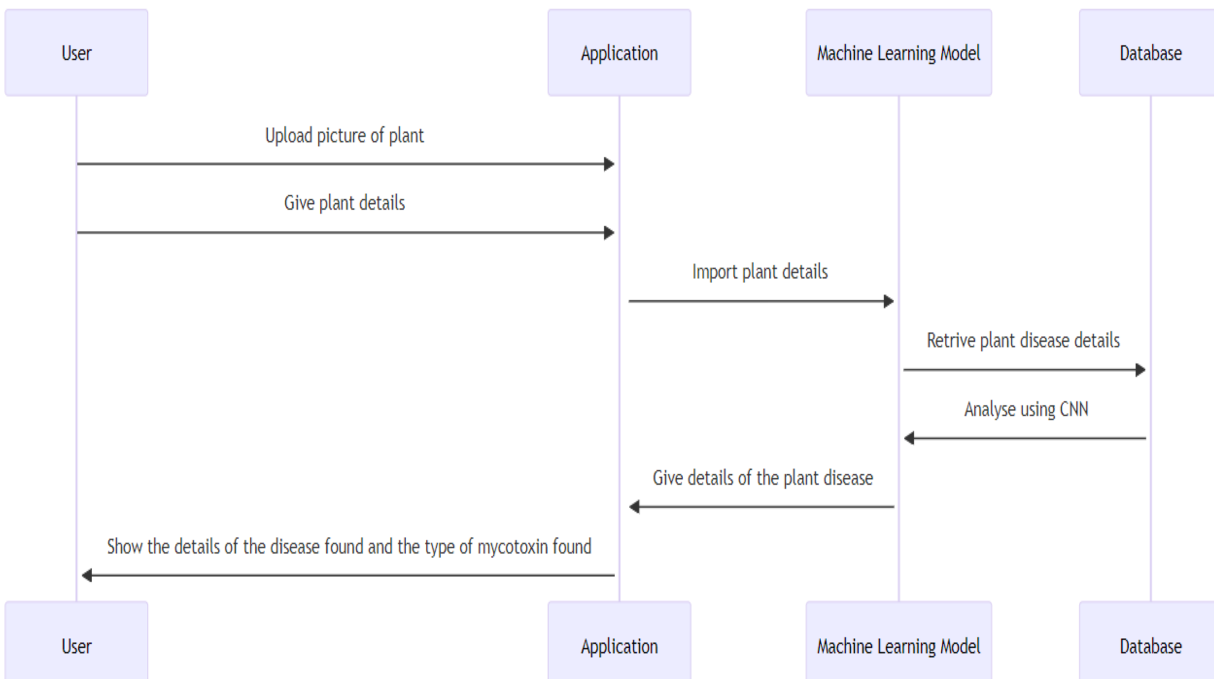


FIG. 3.3 SEQUENCE DIAGRAM

3.5 DEVELOPMENTAL ENVIRONMENT

3.5.1 HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the system's implementation. It should therefore be a complete and consistent specification of the entire system. It is generally used by software engineers as the starting point for the system design.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i5
RAM	8 GB RAM
HARD DISK	512 GB
PROCESSOR SPEED	MINIMUM 1.1 GHz

3.5.2 SOFTWARE REQUIREMENTS

The software requirements document is the specifications of the system. It should include both a definition and a specification of requirements. It is a set of what the system should rather be doing than focus on how it should be done. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating the cost, planning team activities, performing tasks, tracking the team, and tracking the team's progress throughout the development activity.

Python IDLE, and **chrome** would all be required.

CHAPTER 4

PROJECT DESCRIPTION

4.1 METHODOLODGY

The methodology for the project "Mycotoxin Detection in Food Materials" encompasses a multifaceted approach aimed at ensuring food safety and reliability. Utilizing CNNs, the project focuses on detecting mycotoxins present in various food materials. These toxins, produced by fungi, pose significant health risks when ingested, necessitating stringent detection measures. By employing biosensors, the project aims to provide a rapid and sensitive means of identifying mycotoxin contamination in food products.

The integration of many other machine learning techniques enhances the detection process by leveraging a dataset of fungal characteristics. This dataset enables the development of predictive models that aid in the identification of fungal growth, thereby facilitating early intervention and mitigation strategies. The utilization of machine learning not only enhances the accuracy of mycotoxin detection but also streamlines the analysis process, allowing for efficient assessment of food safety.

Moreover, this project extends its impact beyond laboratory settings, benefiting food safety officers, farmers, and consumers alike. By providing timely and reliable detection of mycotoxin contamination, stakeholders can take proactive measures to prevent the distribution of contaminated food products, thereby safeguarding public health and bolstering consumer confidence.

4.2 MODULE DESCRIPTION

1. Introduction to Mycotoxin Detection:

Mycotoxins are harmful compounds produced by fungi that contaminate food, posing serious health risks. This module introduces the significance of detecting mycotoxins in food materials for ensuring food safety. It outlines the importance of this project in aiding food safety officers, farmers, and consumers in identifying and preventing mycotoxin contamination. Furthermore, it emphasizes the utilization of biosensors as a modern approach for mycotoxin detection.

2. Understanding Mycotoxin Detection Techniques:

This module delves into various techniques employed for mycotoxin detection, focusing on biosensors. It elucidates the principles behind biosensor technology and its advantages in terms of sensitivity, specificity, and rapidity. Additionally, it discusses the integration of machine learning algorithms to enhance detection accuracy by analyzing datasets related to fungal growth patterns, aiding in early detection and prevention measures.

3. Development and Optimization of Biosensors :

Here, the process of developing and optimizing biosensors for mycotoxin detection is detailed. It covers aspects such as sensor design, selection of recognition elements (e.g., antibodies or aptamers), and signal transduction mechanisms. Moreover, it emphasizes the importance of calibration and validation to ensure reliable and accurate detection results. This module also discusses strategies for enhancing biosensor performance, such as surface modification and signal amplification techniques.

4. Integration of Machine Learning in Mycotoxin Detection:

This module focuses on the integration of machine learning algorithms in conjunction with biosensors for mycotoxin detection. It explains how machine learning models can analyze complex datasets pertaining to fungal growth dynamics and mycotoxin production, enabling predictive modeling and real-time monitoring. Furthermore, it discusses the training and validation of machine learning models using curated datasets to improve detection sensitivity and specificity.

5. Field Deployment and Validation:

Here, the process of deploying biosensor-based mycotoxin detection systems in real-world settings is outlined. It addresses considerations such as sample preparation, on-site detection protocols, and data interpretation. Moreover, it discusses the importance of validation studies to assess the performance and reliability of the detection system under diverse environmental conditions and food matrices. This module also emphasizes the collaboration with stakeholders, including food safety officers and farmers, for field validation.

6. Impact and Future Directions:

The final module explores the potential impact of the project on food safety practices and public health. It highlights the benefits of early mycotoxin detection in mitigating health risks and ensuring food reliability. Additionally, it discusses future directions, such as the development of portable and affordable detection devices, expanding the scope to detect additional food contaminants, and integrating IoT technologies for remote monitoring. This module concludes by emphasizing the importance of continuous research and innovation in enhancing food safety measures.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 OUTPUT

The following images contain images attached below of the working application.

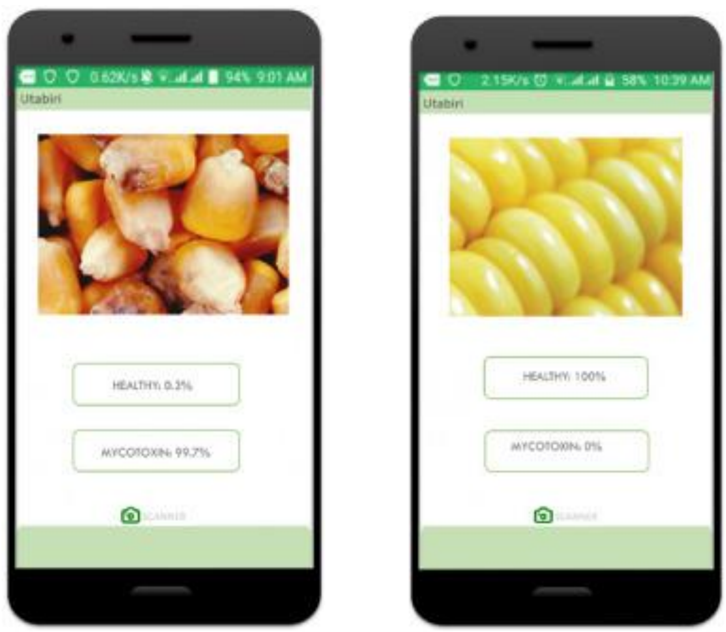


Fig 5.1: Output

5.2 SOURCE CODE:

```
#imports
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout, Conv2D,
    MaxPooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator
#loading directories + data manipulation
train_path = '/Users/ gopika /Deeplearning/fresh_and_rotton/dataset/train'
test_path = '/Users/ gopika /Deeplearning/fresh_and_rotton/dataset/test'
BATCH_SIZE = 10
train_batches = ImageDataGenerator(
   preprocessing_function=tf.keras.applications.vgg16.preprocess_input,
   rescale=1/255.,
   horizontal_flip=True,
   vertical_flip=True
).flow_from_directory(
   directory=train_path,
   target_size=(20, 20),
   classes=['freshapples', 'freshbananas', 'freshcorn', 'rottenapples',
     'rottenbananas','rottencorn'],
   batch_size=BATCH_SIZE,
   class_mode='categorical',
   color_mode='rgb'
)
test_batches = ImageDataGenerator(
   preprocessing_function=tf.keras.applications.vgg16.preprocess_input,
     rescale=1/255.
).flow_from_directory(
   directory=test_path,
   target_size=(20, 20),
   classes=['freshapples', 'freshbananas', 'freshoranges', 'rottenapples',
     'rottenbananas','rottenorganges'],
```

```
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    color_mode='rgb',
    shuffle=False
)
#building the model
model = Sequential()
model.add(Conv2D(32, (3, 3), activation=('relu'), input_shape=(20, 20, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64,(3,3), activation=('relu')))
model.add(MaxPooling2D(2,2))
model.add(Flatten())
model.add(Dense(128, activation=('relu')))
model.add(Dense(128, activation=('relu')))
model.add(Dense(6, activation=('softmax')))
#evaluating the model
model.compile(optimizer='adam', loss='categorical_crossentropy',
     metrics=['accuracy'])
model.fit(test_batches, epochs=17)
```

<u>PyTorch</u>

```
#imports
import torch
from torchvision import datasets, models, transforms, utils
import torch.nn as nn
import torch.optim as optim
import os
import numpy as np
import matplotlib.pyplot as plt
import torch.nn.functional as F
#loading directories + data manipulation
```

```
fruit_train = '/Users/ gopika /Deeplearning/fresh_and_rotton/dataset/train'
fruit_test = '/Users/ gopika /Deeplearning/fresh_and_rotton/dataset/test'
data_dir = "/Users/gopika/Deeplearning/fresh_and_rotton/dataset"
data_transform = {'train':transforms.Compose([
          transforms.Resize((224, 224)),
          transforms.RandomHorizontalFlip(),
          transforms.ToTensor(),
          transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
          ]),
         'test':transforms.Compose([
           transforms.Resize((224, 224)),
           transforms.ToTensor(),
           transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
         ]) }
image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x),
   data_transform[x]) for x in ['train', 'test']}
data_loader = {x:torch.utils.data.DataLoader(image_datasets[x], shuffle=True,
   batch_size=124, num_workers=0) for x in ['train', 'test']}
class_names = image_datasets['train'].classes
#visualization of data
def imshow(inp, title=None):
  inp = inp.numpy().transpose((1, 2, 0))
  mean = np.array([0.485, 0.456, 0.406])
  std = np.array([0.229, 0.224, 0.225])
  inp = std * inp + mean
  inp = np.clip(inp, 0, 1)
  plt.imshow(inp)
  if title is not None:
    plt.title(title)
  plt.pause(0.001)
inputs, classes = next(iter(data_loader['train']))
out = utils.make_grid(inputs)
```

```
imshow(out, title=[class_names[x] for x in classes])
#building the network
class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(16, 8, kernel_size=3, padding=1)
        self.fc1 = nn.Linear(8*56*56, 56) #256
        self.fc2 = nn.Linear(56, 6)
        self.relu = nn.ReLU()
    def forward(self, x):
        x = F.max_pool2d(self.relu(self.conv1(x)), 2)
        x = F.max_pool2d(self.relu(self.conv2(x)), 2)
        x = torch.flatten(x, 1)
        x = self.relu(self.fc1(x))
        x = self.fc2(x)
        return x
net = Net()
optimizer = optim.Adam(net.parameters(), lr=0.0001)
cross_el = nn.CrossEntropyLoss()
EPOCHS = 8
#training the model
for epoch in range(EPOCHS):
    net.train()
    for data in data_loader['train']:
        x, y = data
        net.zero_grad()
        output = net(x)
        loss = cross_el(output, y)
        loss.backward()
        optimizer.step()
correct = 0
```

```
total = 0
#testing the model
with torch.no_grad():
    for data in data_loader['test']:
        x, y = data
        output = net(x)
        for idx, i in enumerate(output):
            if torch.argmax(i) == y[idx]:
                correct +=1
            total +=1
      print(f’accuracy: {round(correct/total, 3)}')
```

<u>//Building The CNN Model</u>

<u>//TensorFlow</u>

```
model = Sequential()
model.add(Conv2D(32, (3, 3), activation=('relu'), input_shape=(20, 20, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64,(3,3), activation=('relu')))
model.add(MaxPooling2D(2,2))
model.add(Flatten())
model.add(Dense(128, activation=('relu')))
model.add(Dense(128, activation=('relu')))
model.add(Dense(6, activation=('softmax')))
model.compile(optimizer='adam', loss='categorical_crossentropy',
      metrics=['accuracy'])
model.fit(test_batches, epochs=17)

model = Sequential()
model.add(Conv2D(32, (3, 3), activation=('relu'), input_shape=(20, 20, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64,(3,3), activation=('relu')))
model.add(MaxPooling2D(2,2))
```

```
model.add(Flatten())
model.add(Dense(128, activation=('relu')))
model.add(Dense(128, activation=('relu')))
model.add(Dense(6, activation=('softmax')))

model.compile(optimizer='adam', loss='categorical_crossentropy',
    metrics=['accuracy'])
model.fit(test_batches, epochs=17)
```

PyTorch

```
class Net(nn.Module):
  def __init__(self):
    super().__init__()
    self.conv1 = nn.Conv2d(3, 16, kernel_size=3, padding=1)
    self.conv2 = nn.Conv2d(16, 8, kernel_size=3, padding=1)
    self.fc1 = nn.Linear(8*56*56, 56) #256
    self.fc2 = nn.Linear(56, 6)
    self.relu = nn.ReLU()
  def forward(self, x):
    x = F.max_pool2d(self.relu(self.conv1(x)), 2)
    x = F.max_pool2d(self.relu(self.conv2(x)), 2)
    x = torch.flatten(x, 1)
    x = self.relu(self.fc1(x))
    x = self.fc2(x)
    return x
net = Net()
optimizer = optim.Adam(net.parameters(), lr=0.0001)
cross_el = nn.CrossEntropyLoss()
EPOCHS = 20
for epoch in range(EPOCHS):
  net.train()
```

```
    for data in data_loader['train']:
        x, y = data
        net.zero_grad()
        output = net(x)
        loss = cross_el(output, y)
        loss.backward()
        optimizer.step()
correct = 0
total = 0
with torch.no_grad():
    for data in data_loader['test']:
        x, y = data
        output = net(x)
        for idx, i in enumerate(output):
            if torch.argmax(i) == y[idx]:
                correct +=1
            total +=1
print(f'accuracy: {round(correct/total, 3)}')
class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(16, 8, kernel_size=3, padding=1)
        self.fc1 = nn.Linear(8*56*56, 56)
        self.fc2 = nn.Linear(56, 6)
        self.relu = nn.ReLU()
class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(16, 8, kernel_size=3, padding=1)
```

```
self.fc1 = nn.Linear(8*56*56, 56)
        self.fc2 = nn.Linear(56, 6)
        self.relu = nn.ReLU()

def forward(self, x):
        x = F.max_pool2d(self.relu(self.conv1(x)), 2)
        x = F.max_pool2d(self.relu(self.conv2(x)), 2)
        x = torch.flatten(x, 1)
        x = self.relu(self.fc1(x))
        x = self.fc2(x)
        return x
net = Net()
optimizer = optim.Adam(net.parameters(), lr=0.0001)
cross_el = nn.CrossEntropyLoss()
EPOCHS = 8

//This is our training loop. Essentially we will run our model and train it using
      the training data, using gradient descent, and or loss function.

for epoch in range(EPOCHS):
    net.train()
    for data in data_loader['train']:
        x, y = data
        net.zero_grad()
        output = net(x)
        loss = cross_el(output, y)
        loss.backward()
        optimizer.step()

correct = 0
total = 0
with torch.no_grad():
```

```
    for data in data_loader['test']:
        x, y = data
        output = net(x)
        for idx, i in enumerate(output):
            if torch.argmax(i) == y[idx]:
                correct +=1
            total +=1
print(f'accuracy: {round(correct/total, 3)}')
```

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

The project on mycotoxin detection in food materials stands as a pivotal endeavor in ensuring food safety and reliability for consumers worldwide. By utilizing biosensors, this initiative addresses the pressing need for rapid and efficient detection of mycotoxins, harmful compounds produced by fungi that can contaminate various food products. Through the integration of machine learning algorithms with datasets pertaining to fungal growth, the project not only facilitates accurate detection but also enables proactive measures to mitigate the risks associated with mycotoxin contamination.

In conclusion, the implementation of biosensors coupled with machine learning techniques represents a significant advancement in the field of food safety. By providing timely and reliable detection of mycotoxins, this project empowers food safety officers, farmers, and consumers to make informed decisions regarding food consumption and production practices. Moreover, it underscores the importance of interdisciplinary approaches in addressing complex challenges within the food industry.

Looking towards the future, further enhancements and refinements to the existing framework hold immense potential for improving food safety standards on a global scale. Continued research and development efforts can lead to the creation of more sensitive and versatile biosensors capable of detecting an even broader range of mycotoxins across various food matrices. Additionally, advancements in machine learning algorithms can further enhance the accuracy and efficiency of detection methods, ultimately streamlining the process of identifying and mitigating mycotoxin contamination.

Furthermore, the integration of emerging technologies such as Internet of Things (IoT) and blockchain can revolutionize the monitoring and traceability of food products from farm to fork. By leveraging IoT devices for real-time monitoring of environmental conditions and supply chain logistics, stakeholders can proactively identify and address potential sources of contamination. Meanwhile, blockchain technology offers an immutable ledger for documenting every step of the food production and distribution process, ensuring transparency and accountability throughout the supply chain.

In essence, the ongoing evolution of mycotoxin detection technologies not only safeguards public health but also fosters greater trust and confidence in the food supply. By embracing innovation and collaboration, we can continue to enhance food safety measures and uphold the highest standards of quality and reliability for consumers worldwide.

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