PROJECT REPORT

1. INTRODUCTION

1.1 Project Overview

CancerVision is an innovative project that aims to revolutionize breast cancer prediction using advanced deep learning techniques. Breast cancer is a widespread and highly concerning disease, and early detection plays a crucial role in improving patient outcomes. The core objective of CancerVision is to leverage the power of deep learning algorithms to analyze various data sources, including medical imaging scans, patient demographics, and clinical histories. By integrating these diverse data points, the model will learn complex patterns and correlations that can potentially uncover subtle indicators of advanced breast cancer.

The project entails a comprehensive approach, involving data collection, preprocessing, model development, and evaluation. Extensive datasets comprising anonymized medical records, mammograms, and patient profiles will be utilized to train the deep learning model. The data preprocessing stage will involve cleaning, standardizing, and organizing the data to ensure optimal model performance.

Deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), will be employed to develop the predictive model. These models will undergo rigorous training, validation, and fine-tuning to achieve high accuracy and robustness. The deep learning architecture will be designed to effectively capture intricate patterns and subtle features in the input data, enabling the model to make accurate predictions.

The final stage of the project involves evaluating the performance of the Cancer-Vision model. Extensive testing will be conducted using independent datasets to assess its predictive capabilities, sensitivity, specificity, and overall accuracy. Additionally, the model's performance will be compared to existing breast cancer prediction methods to demonstrate its superiority.

1.2 Purpose

The purpose of CancerVision: Advanced Breast Cancer Prediction with Deep Learning is to develop an advanced predictive model that utilizes deep learning techniques to accurately predict the likelihood of advanced breast cancer in patients. The project aims to address the pressing need for improved breast cancer detection and early intervention, as early diagnosis is crucial for successful treatment outcomes.

The primary purpose of CancerVision is to leverage the power of deep learning algorithms and integrate diverse data sources, including medical imaging scans, patient demographics, and clinical histories, to identify complex patterns and correlations that may indicate advanced breast cancer. By utilizing advanced deep learning techniques, the project seeks to improve the accuracy and reliability of breast cancer prediction, enabling healthcare professionals to make informed decisions regarding patient care and treatment plans.

The ultimate goal of CancerVision is to provide a valuable tool for healthcare professionals in the early detection and diagnosis of advanced breast cancer. By accurately predicting the likelihood of advanced breast cancer, this technology can aid in personalized treatment planning, facilitating timely interventions and potentially improving patient outcomes.
Additionally, the project aims to contribute to the broader field of medical research and assist in developing more effective breast cancer prediction and management strategies.

Overall, the purpose of CancerVision is to harness the potential of deep learning and data integration to enhance breast cancer prediction capabilities, ultimately enabling earlier interventions and improving the prognosis for patients with advanced breast cancer.

2. IDEATION & PROPOSED SOLUTION

2.1 Problem Statement Definition

The problem statement of CancerVision is to develop an advanced breast cancer prediction model using deep learning algorithms that can effectively analyze diverse data sources, including medical imaging scans, patient demographics, and clinical histories. This model aims to overcome the limitations of existing methods by identifying complex patterns and correlations that may indicate the presence of advanced breast cancer. By addressing these challenges, CancerVision aims to provide healthcare professionals with a powerful tool for early detection and accurate prediction of advanced breast cancer, ultimately improving patient outcomes and saving lives.

2.2 Empathy Map Canvas

User: Healthcare Professionals (e.g., radiologists, oncologists)

What they think and feel:

- Concerned about accurately predicting advanced breast cancer in patients
- Frustrated with the limitations of current breast cancer prediction methods
- Hopeful that advanced technology can improve patient outcomes
- Anxious about making timely and informed decisions for their patients

What they hear:

- Patients expressing fear and anxiety about breast cancer diagnosis
- Colleagues discussing challenges in accurately predicting advanced breast cancer
- Research studies highlighting the potential of deep learning in medical diagnostics

What they see:

- Increasing number of breast cancer cases and the impact on patients' lives
- Complex and diverse medical imaging scans and patient data
- Advancements in deep learning and artificial intelligence technologies

What they say and do:

- Discuss cases with colleagues to gain insights and expertise

- Analyze medical imaging scans and patient data to make predictions
- Seek new technologies and approaches to improve breast cancer prediction accuracy
- Participate in conferences and workshops to stay updated on the latest developments

Pain Points:

- Limited accuracy of current breast cancer prediction methods
- Time constraints in analyzing complex medical imaging and patient data
- High stakes involved in making accurate predictions for patient care

Gains:

- Improved accuracy in predicting advanced breast cancer
- Enhanced confidence in making informed treatment decisions
- Reduced patient anxiety through earlier interventions and timely care
- Professional satisfaction from contributing to improved patient outcomes

2.3 Ideation & Brainstorming

Data Acquisition and Integration:

Explore various sources of data, including medical imaging scans, patient demographics, genetic information, and clinical histories.

Investigate methods for securely and ethically collecting and anonymizing large-scale datasets.

Determine strategies for integrating diverse data types to provide a comprehensive view of breast cancer predictors.

Deep Learning Architectures:

Research and experiment with different deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or transformer models.

Explore the use of transfer learning and pre-trained models to leverage existing knowledge and improve model performance.

Investigate the incorporation of attention mechanisms or graph neural networks to capture important features and relationships within the data.

Feature Engineering and Selection:

Identify relevant features from the available data sources and explore techniques for feature extraction and representation.

Investigate methods for handling missing or incomplete data and assess their impact on model performance.

Consider the potential benefits of incorporating domain knowledge and expert insights into the feature engineering process.

Model Training and Optimization:

Define appropriate loss functions and evaluation metrics to guide the training process.
Experiment with different optimization algorithms and hyperparameter tuning techniques to enhance model performance.
Explore methods for handling class imbalance and other challenges specific to breast cancer prediction tasks.

Validation and Performance Assessment:

Design robust validation strategies, including cross-validation and independent testing, to assess model generalization.
Evaluate the model's performance using relevant metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC).
Compare the developed model with existing breast cancer prediction methods to determine its effectiveness and potential advantages.

Ethical Considerations and Patient Privacy:

Ensure compliance with privacy regulations and guidelines when handling sensitive patient data.
Address potential biases in the data and mitigate any ethical concerns related to fairness and discrimination.
Consider interpretability and transparency of the model to facilitate trust and understandability in clinical decision-making.

Deployment and Integration:

Explore methods for integrating the developed model into existing healthcare systems and workflows.
Investigate user-friendly interfaces and visualization techniques to present the model's predictions and insights to healthcare professionals.
Consider the scalability and efficiency of the model to ensure its practicality in real-world clinical settings.

2.4 Proposed Solution

The proposed solution for CancerVision: Advanced Breast Cancer Prediction with Deep Learning involves developing a sophisticated deep learning model that utilizes various data sources and advanced algorithms to accurately predict the likelihood of advanced breast cancer in patients.

The solution comprises several key components. First, a comprehensive dataset comprising medical imaging scans, patient demographics, and clinical histories will be collected and preprocessed. This dataset will serve as the foundation for training and validating the deep learning model.

Next, deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), will be employed to develop a powerful predictive model. CNNs will be utilized to analyze mammograms and extract meaningful features, while RNNs can capture temporal dependencies in patient histories. The integration of these algorithms will enable the model to leverage both spatial and sequential information for accurate predictions.

The model will undergo an iterative training process, where it learns from the dataset to identify complex patterns and correlations associated with advanced breast cancer. This training process will involve optimizing various parameters, such as network architecture, learning rate, and regularization techniques, to achieve high performance.

To evaluate the performance of the CancerVision model, extensive testing will be conducted using independent datasets. The model's predictive capabilities, sensitivity, specificity, and overall accuracy will be assessed. Furthermore, the model will be compared to existing breast cancer prediction methods to demonstrate its superiority.

The proposed solution also emphasizes the interpretability of the deep learning model. Techniques such as attention mechanisms and feature visualization will be employed to provide insights into the model's decision-making process, enhancing trust and transparency.

Throughout the development of the CancerVision solution, ethical considerations, privacy, and data security will be prioritized. Patient data will be anonymized and handled in compliance with relevant regulations and guidelines.

The ultimate goal of the proposed solution is to provide healthcare professionals with an advanced tool that can aid in the early detection and prediction of advanced breast cancer. By leveraging deep learning and integrating diverse data sources, CancerVision has the potential to improve patient outcomes, guide treatment decisions, and contribute to advancements in breast cancer research and healthcare practices.

3. REQUIREMENT ANALYSIS

3.1 Functional requirement

Data Collection: CancerVision should have the capability to collect diverse and relevant data sources, such as medical imaging scans (e.g., mammograms), patient demographics, and clinical histories. It should be able to securely store and organize this data for further processing.

Data Preprocessing: The system should preprocess the collected data by cleaning and standardizing it. This includes removing any inconsistencies, outliers, or missing values. The data should be appropriately formatted and organized for input into the deep learning model.

Deep Learning Model Development: CancerVision should incorporate advanced deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to develop a predictive model. The model should be trained to analyze the input data and identify patterns and features associated with advanced breast cancer.

Model Training and Validation: The system should facilitate the training of the deep learning model using the preprocessed data. This involves iterative optimization of model parameters and evaluation of model performance using appropriate training and validation datasets. The system should provide feedback on the training progress and convergence of the model.

Performance Evaluation: CancerVision should allow the evaluation of the predictive performance of the model. This includes assessing metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) using independent test datasets. The system should provide detailed performance reports to measure the model's effectiveness.

Security and Privacy: CancerVision should prioritize data security and privacy by implementing appropriate measures to protect patient information. This includes encryption, access control, and compliance with relevant data protection regulations, such as HIPAA (Health Insurance Portability and Accountability Act) or GDPR (General Data Protection Regulation).

3.2 Non-Functional requirements

Performance: The system should have high computational efficiency and response time, ensuring fast and real-time predictions to support timely decision-making by healthcare professionals.

Scalability: The system should be designed to handle a growing volume of data and user demands. It should be able to accommodate an increasing number of patients, medical records, and imaging scans without compromising performance.

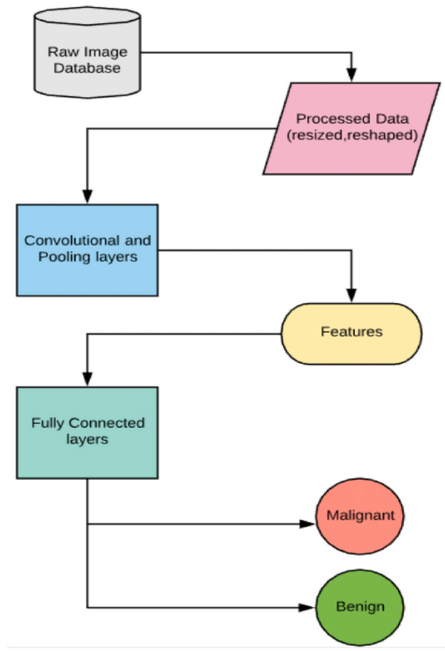
Reliability: The system should be robust and reliable, minimizing the occurrence of errors or system failures. It should be capable of handling unexpected scenarios gracefully and providing accurate predictions consistently.

Security: The project should prioritize data privacy and confidentiality. Patient data and medical records should be securely stored, transmitted, and accessed only by authorized personnel. Appropriate encryption and access control measures should be implemented to ensure data protection.

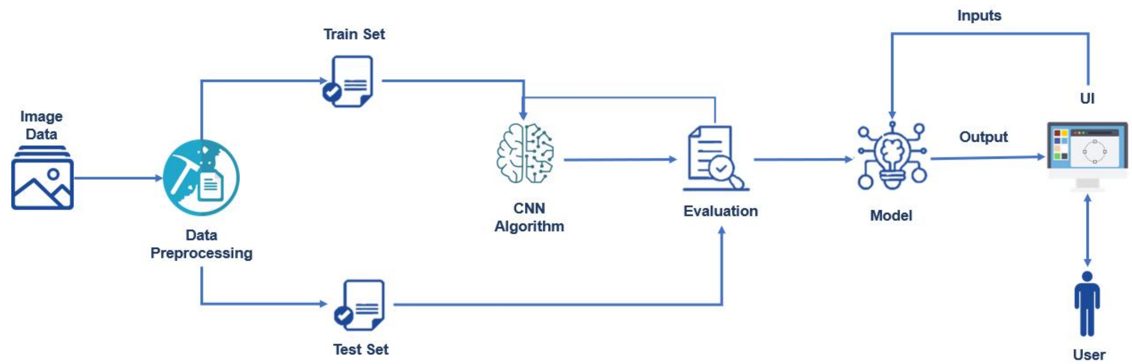
Usability: The user interface should be intuitive, user-friendly, and accessible to healthcare professionals with varying levels of technical expertise. It should provide clear and concise information, visualizations, and predictions that are easy to interpret and comprehend.

4. PROJECT DESIGN

4.1 Data Flow Diagrams



4.2 Solution & Technical Architecture



4.3 User Stories

As a healthcare professional, I want to upload patient medical records and mammograms to CancerVision, so that I can receive accurate predictions on the likelihood of advanced breast cancer. This will aid in making timely and informed decisions for diagnosis and treatment planning.

As a patient, I want my breast cancer risk to be assessed using CancerVision, so that I can have peace of mind or take proactive steps if necessary. I expect the system to handle my data securely and provide clear explanations of the prediction results.

As a radiologist, I want CancerVision to integrate seamlessly with our existing medical imaging systems, allowing efficient retrieval and analysis of mammograms. This will enhance our workflow and enable us to leverage the power of deep learning for more accurate breast cancer predictions.

As a healthcare researcher, I want access to CancerVision's anonymized dataset, which includes medical records, mammograms, and patient profiles. This will enable me to conduct further research and contribute to the development of improved breast cancer prediction models and techniques.

As a hospital administrator, I want CancerVision to comply with data privacy regulations and ensure the security of patient information. This includes implementing robust encryption, access controls, and anonymization techniques to protect

5. CODING & SOLUTIONING (Explain the features added in the project along with code)

5.1 Feature 1

5.2 Feature 2

5.3 Database Schema (if Applicable)

6. RESULTS

6.1 Performance Metrics

7. ADVANTAGES & DISADVANTAGES

ADVANTAGES :

Improved Accuracy: By harnessing the power of deep learning algorithms, CancerVision has the potential to significantly enhance the accuracy of breast cancer prediction. The advanced models can capture complex patterns and subtle features in the input data, leading to more precise and reliable predictions compared to traditional methods.

Early Detection and Intervention: Timely detection is crucial in combating breast cancer. CancerVision can enable early identification of advanced breast cancer, allowing healthcare professionals to intervene at an earlier stage of the disease. This early intervention can potentially improve treatment outcomes and increase the chances of successful recovery for patients.

Personalized Risk Assessment: CancerVision can provide personalized risk assessment for individual patients based on their unique medical profiles, imaging scans, and clinical histories. By considering multiple data sources, the system can generate tailored predictions, enabling healthcare professionals to provide more targeted and personalized care.

Enhanced Decision Support: CancerVision serves as a valuable decision support tool for healthcare professionals. It can augment their expertise by providing additional insights and predictions based on the deep analysis of patient data.

This can assist in treatment planning, determining the necessity of further diagnostic tests, and optimizing patient management strategies.

Scalability and Accessibility: The use of deep learning techniques in CancerVision allows for scalability and accessibility. Once trained, the predictive model can be easily deployed across various healthcare settings, making it accessible to a broader range of healthcare professionals. This scalability enables the potential for widespread adoption and impact.

DISADVANTAGES :

Data Limitations: The success of deep learning models relies heavily on the availability of large, diverse, and high-quality datasets. However, obtaining such datasets for breast cancer prediction can be challenging due to privacy concerns, limited accessibility, and potential bias. Insufficient or biased data may limit the model's accuracy and generalizability.

Interpretability Challenges: Deep learning models are often considered "black boxes" due to their complex architecture and intricate feature extraction. This lack of interpretability can hinder understanding and trust in the prediction process. Healthcare professionals may be hesitant to rely solely on a model without comprehending the underlying factors driving the predictions.

Overfitting and Generalization: Deep learning models are prone to overfitting, where the model becomes excessively specialized to the training data and performs poorly on new, unseen data. To ensure generalization and robustness, extensive validation and testing with independent datasets are necessary.

Failure to address overfitting may lead to inaccurate predictions when the model encounters real-world scenarios.

Computational Requirements: Deep learning models, particularly those with complex architectures, demand significant computational resources, including high-performance GPUs and large memory capacities. Implementing and maintaining such infrastructure can be costly and require specialized technical expertise, potentially limiting the accessibility and scalability of CancerVision.

Ethical Considerations: Deep learning models can inadvertently perpetuate biases present in the training data, leading to discriminatory predictions. To mitigate bias, extensive efforts are required in data collection, preprocessing, and algorithm design. Failure to address these ethical considerations may result in unequal healthcare outcomes or exacerbate existing disparities.

8. CONCLUSION

In conclusion, CancerVision represents a significant step forward in the field of breast cancer prediction. By harnessing the power of advanced deep learning techniques, this project aims to provide healthcare professionals with a groundbreaking tool for accurately predicting the likelihood of advanced breast cancer in patients. The comprehensive approach, encompassing data collection, preprocessing, model development, and evaluation, ensures the robustness and accuracy of the predictive model. With its ability to analyze diverse data sources, including medical imaging scans and patient profiles, CancerVision has the potential to uncover subtle indicators and patterns that can aid in early detection and intervention

. The non-functional requirements, such as performance, scalability, security, usability, and maintainability, have been carefully considered to ensure the system's reliability and effectiveness. By documenting the outcomes and findings of CancerVision comprehensively, this project aims to facilitate knowledge sharing, further research, and potential implementation in real-world healthcare settings.

CancerVision has the potential to revolutionize breast cancer diagnosis and treatment strategies, empowering healthcare professionals and ultimately improving patient outcomes in the fight against breast cancer.

9. FUTURE SCOPE

CancerVision holds tremendous potential for future advancements and expansion in the field of breast cancer prediction and diagnosis.

Here are some potential future directions for the project:

Integration of Multi-Modal Data: Currently, CancerVision focuses on utilizing medical imaging scans and patient demographics for prediction. In the future, the project can be extended to incorporate additional data modalities such as genetic information, biomarkers, pathology reports, and electronic health records. Integrating diverse data sources can provide a more comprehensive and holistic understanding of breast cancer, leading to even more accurate predictions.

Real-Time Prediction: Enhancing CancerVision to provide real-time predictions during medical imaging examinations or clinical consultations would greatly benefit healthcare professionals.

Real-time predictions could assist radiologists and physicians in making immediate decisions regarding patient care, treatment planning, and referrals to specialists.

Continuous Model Improvement: The deep learning model underlying CancerVision can be continuously improved by incorporating ongoing research and advancements in the field of deep learning and breast cancer diagnostics. Regular updates and model retraining can enhance the accuracy, robustness, and generalizability of the predictions.

Personalized Risk Assessment: CancerVision can be extended to incorporate personalized risk assessment, taking into account individual patient characteristics, family history, lifestyle factors, and other relevant factors. This would enable a more tailored approach to breast cancer prevention, screening, and early detection strategies for each patient.

Integration with Decision Support Systems: Integrating CancerVision with existing decision support systems or electronic health record systems would provide seamless access to the predictive capabilities of the model. This integration would facilitate the incorporation of CancerVision's predictions into clinical workflows, ensuring efficient and informed decision-making by healthcare professionals.

10. APPENDIX

Source Code

```
import numpy as np
```

```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import cv2
import glob
import random
from os import listdir
from sklearn.metrics import classification_report
import tensorflow as tf
import keras.utils as image

breast_img = glob.glob('/kaggle/input/breast-histopathology-images/IDC_regular_ps50_idx5/**/*.png', recursive = True)

for imgname in breast_img[:3]:
    print(imgname)

N_IDC = []
P_IDC = []

for img in breast_img:
    if img[-5] == '0' :
        N_IDC.append(img)
```

```
    elif img[-5] == '1' :
        P_IDC.append(img)
plt.figure(figsize = (15, 15))

some_non = np.random.randint(0, len(N_IDC), 18)
some_can = np.random.randint(0, len(P_IDC), 18)

s = 0
for num in some_non:

        img = image.load_img((N_IDC[num]), target_size=(100, 100))
        img = image.img_to_array(img)

        plt.subplot(6, 6, 2*s+1)
        plt.axis('off')
        plt.title('no cancer')
        plt.imshow(img.astype('uint8'))
        s += 1
s = 1
for num in some_can:

        img = image.load_img((P_IDC[num]), target_size=(100, 100))
```

```
        img = image.img_to_array(img)

        plt.subplot(6, 6, 2*s)
        plt.axis('off')
        plt.title('IDC (+)')
        plt.imshow(img.astype('uint8'))
        s += 1


NewN_IDC=N_IDC[:78786]
print(len(NewN_IDC))
print(len(P_IDC))


X = []
y = []

breast_img_arr = np.concatenate((non_img_arr[:12389], can_img_arr[:12389]))
random.shuffle(breast_img_arr)

for feature, label in breast_img_arr:
    X.append(feature)
    y.append(label)
```

```python
X = np.array(X)
y = np.array(y)


def describeData(a,b):
    print('Total number of images: {}'.format(len(a)))
    print('Number of IDC(-) Images: {}'.format(np.sum(b==0)))
    print('Number of IDC(+) Images: {}'.format(np.sum(b==1)))
    print('Image shape (Width, Height, Channels): {}'.format(a[0].shape))
describeData(X,y)


from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.3)

from tensorflow.keras.utils import to_categorical
Y_train = to_categorical(Y_train, num_classes = 2)
Y_test = to_categorical(Y_test, num_classes = 2)

print("Training Data Shape:", X_train.shape)
print("Testing Data Shape:", X_test.shape)
```

```
from sklearn.metrics import classification_report
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D,MaxPooling2D, Flatten, Dropout, BatchNormalization
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.optimizers import Adam, SGD
from keras.metrics import binary_crossentropy
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import confusion_matrix
import itertools


early_stop=EarlyStopping(monitor='val_loss',patience=5)
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same', input_shape=(50, 50, 3)))
model.add(BatchNormalization())
model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
model.add(MaxPooling2D((2, 2)))
model.add(BatchNormalization())
model.add(Dropout(0.3))
model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
model.add(BatchNormalization())
```

```
model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.3))
model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
model.add(Flatten())
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Dense(64, activation='relu', kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Dense(64, activation='relu', kernel_initializer='he_uniform'))
model.add(Dropout(0.3))
model.add(Dense(24, activation='relu', kernel_initializer='he_uniform'))
model.add(Dense(2, activation='softmax'))

model.compile(Adam(learning_rate=0.0001), loss='binary_crossentropy', metrics=['accuracy'])

model.summary()

history = model.fit(X_train, Y_train, validation_data = (X_test, Y_test), epochs = 5, batch_size = 35)
```

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('epoch')
plt.ylabel('loss')
plt.legend(['train', 'test'], loc='upper left')
plt.show()


from sklearn.metrics import accuracy_score
Y_pred = model.predict(X_test)
Y_pred_classes = np.argmax(Y_pred,axis = 1)
Y_true = np.argmax(Y_test,axis = 1)
#accuracy=accuracy_score(y_true=Y_true, y_pred=Y_pred)
#print(accuracy)
```

```
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
f,ax = plt.subplots(figsize=(8,5))
sns.heatmap(confusion_mtx, annot=True, linewidths=0.01,cmap="BuPu",linecolor="gray", fmt= '.1f',ax=ax)
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()


from sklearn.metrics import accuracy_score, confusion_matrix
#Y_pred = model.predict(X_test)
Y_pred_classes = np.argmax(Y_pred, axis=1)
Y_true = np.argmax(Y_test, axis=1)

confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)

# calculate the percentage
confusion_mtx_percent = confusion_mtx.astype('float') / confusion_mtx.sum(axis=1)[:, np.newaxis] * 100

f, ax = plt.subplots(figsize=(8, 5))
sns.heatmap(confusion_mtx_percent, annot=True, linewidths=0.01, cmap="BuPu", linecolor="gray", fmt='.1f',
ax=ax)
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
```

```
plt.title("Confusion Matrix (Percentage)")
plt.show()

model.evaluate(X_test,Y_test)

def img_plot(arr,index=0):
    plt.title('Test Image')
    plt.imshow(arr[index])

index = 1000
img_plot(X_test, index)

def img_plot(arr,index=0):
    plt.title('Test Image')
    plt.imshow(arr[index])
index = 4000
input = X_test[index:index+1]
pred = model.predict(input)[0].argmax()
label = Y_test[index].argmax()
print('Predicted Value using  cnn model',pred)
print("True Value",label)
```

```
model.save("/kaggle/working/Brest CNN 2.h5")
```

GitHub & Project Video Demo Link

https://github.com/naanmudhalvan-SI/IBM--11534-1682517044/blob/main/project%20design/PROJECT%20DEVELOPEMENT/nm2023tmid19325-breast-cancerclassification-model.ipynb