

Panimalar Engineering College
21CS1512 Socially Relevant Mini Project

ORAL CANCER CLASSIFICATION AND DETECTION

Batch – C20

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ABSTRACT

- Oral cancer remains a significant public health concern, necessitating timely detection and accurate classification to improve patient outcomes.
- The project presents a novel approach for oral cancer classification and detection utilizing Convolutional Neural Networks (CNNs) for feature extraction combined with K-means clustering for classification.
- We first employ a CNN to automatically extract pertinent features from oral cancer images, leveraging its ability to learn complex patterns from the data.
- Subsequently, we implement the K-means algorithm to cluster the extracted features, enabling effective categorization of the images into benign and malignant classes.
- Our methodology was evaluated on a dataset of oral images, and the results demonstrated superior accuracy compared to traditional classification methods.
- This approach not only enhances the efficiency of oral cancer detection but also holds promise for integration into clinical practice, facilitating earlier diagnosis and treatment planning.
- The findings underscore the potential of combining deep learning techniques with unsupervised clustering methods in medical imaging applications



Introduction

- Accurately identifying oral lesions early is crucial for effective intervention and management. Early-stage oral cancer is often asymptomatic, making detection difficult without advanced diagnostic tools.
- Therefore, there is a pressing need for innovative and reliable methods to facilitate the early diagnosis of oral cancer, allowing for timely treatment and better patient outcomes.
- Recent advancements in machine learning, especially within medical imaging, have created new opportunities for improving diagnostic accuracy. Convolutional neural networks (CNNs) have become powerful tools for image analysis, adept at automatically learning features from extensive datasets. Their capacity to process and classify images with high precision has been successfully utilized across multiple fields, including oncology.
- However, despite their strength in feature extraction, classifying these features can still present challenges.



Existing system

- Convolutional Neural Networks (CNNs) are a well established AI algorithm that mimics the functioning of human neurons and is essential in AI research. Recent studies are employing CNN techniques to assist physicians in tackling various challenges and enhancing diagnostic accuracy through radiographic and clinical imaging.
- Researchers have discovered that CNN methods like Faster R-CNN and DenseNet can reach expert-level performance in detecting lesions in chest X-rays, clinical images of skin lesions, laryngeal injuries, cervical lesions, and esophageal images. This advancement underscores the potential of AI technologies—particularly CNNs—to improve diagnostic accuracy and support healthcare professionals. [

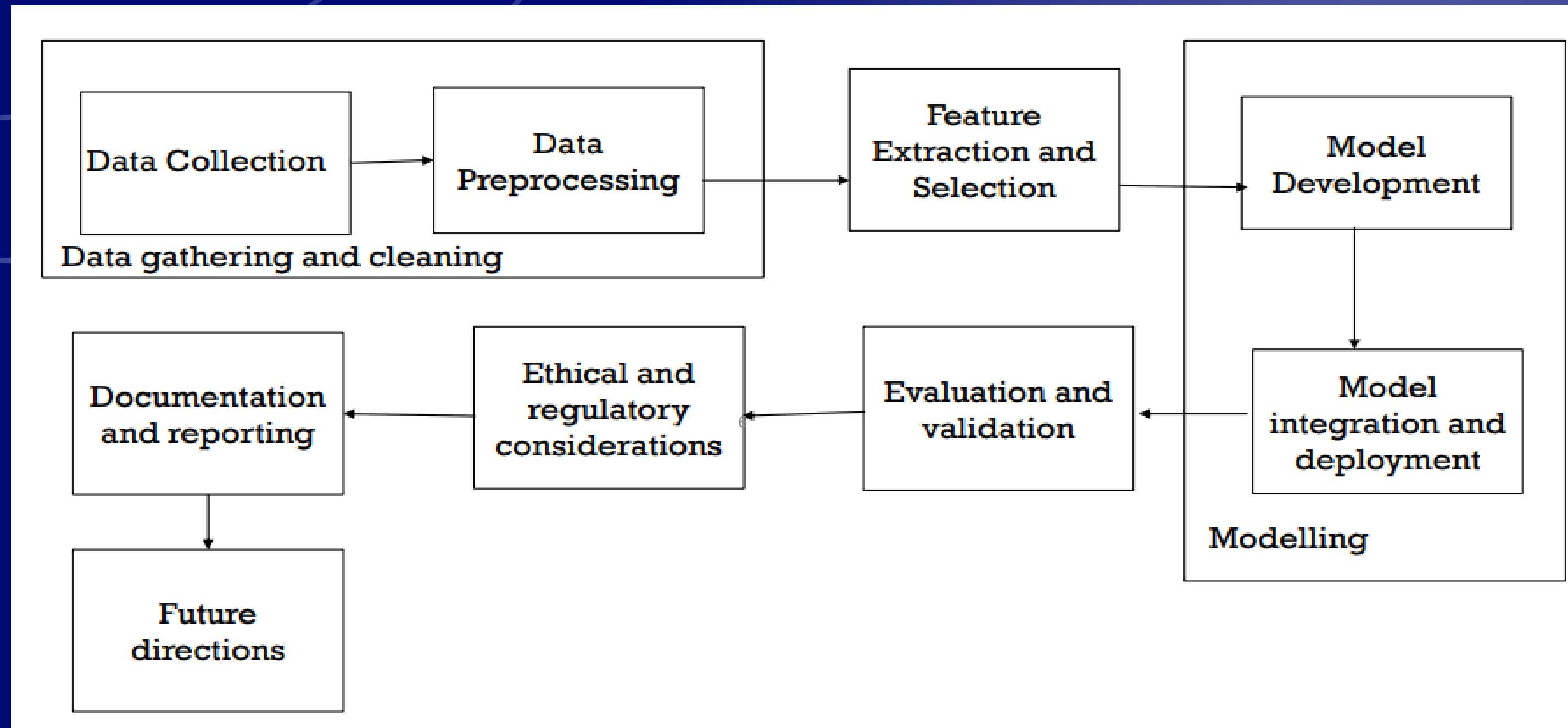


Proposed System

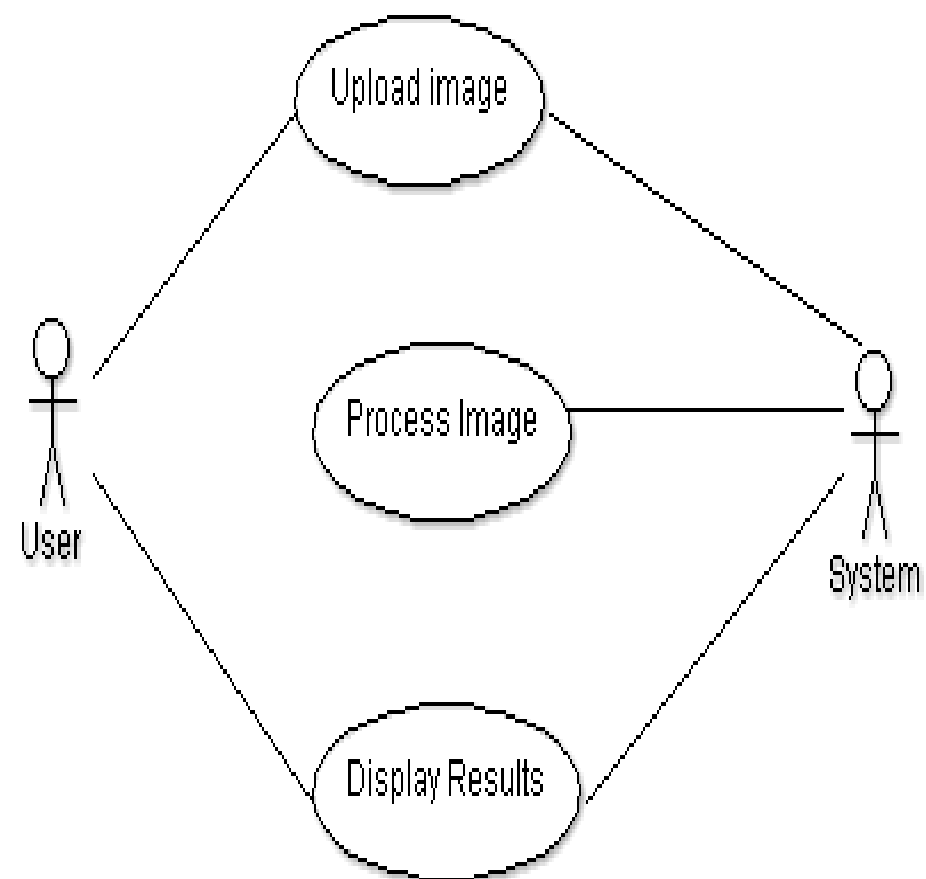
- The architecture of our proposed hybrid model, which integrates Convolutional Neural Networks (CNNs) for feature extraction and K-means clustering for classification.
- The input layer accepts oral images in grayscale format, sized at 224x224 pixels. The model includes three convolutional layers, each accompanied by ReLU activation functions, enabling the model to learn hierarchical features from the images. Following each convolutional layer is a max pooling layer, which reduces spatial dimensions and computational complexity.
- Next, the flattened output is processed by two fully connected layers with 32 and 64 neurons, respectively, leading to a dense output layer that classifies the features as either benign or malignant. Finally, the features extracted from the CNN are clustered using the K-means algorithm, which groups the images based on feature similarity, thereby improving the efficiency of the classification process.



ARCHITECTURE DIAGRAM



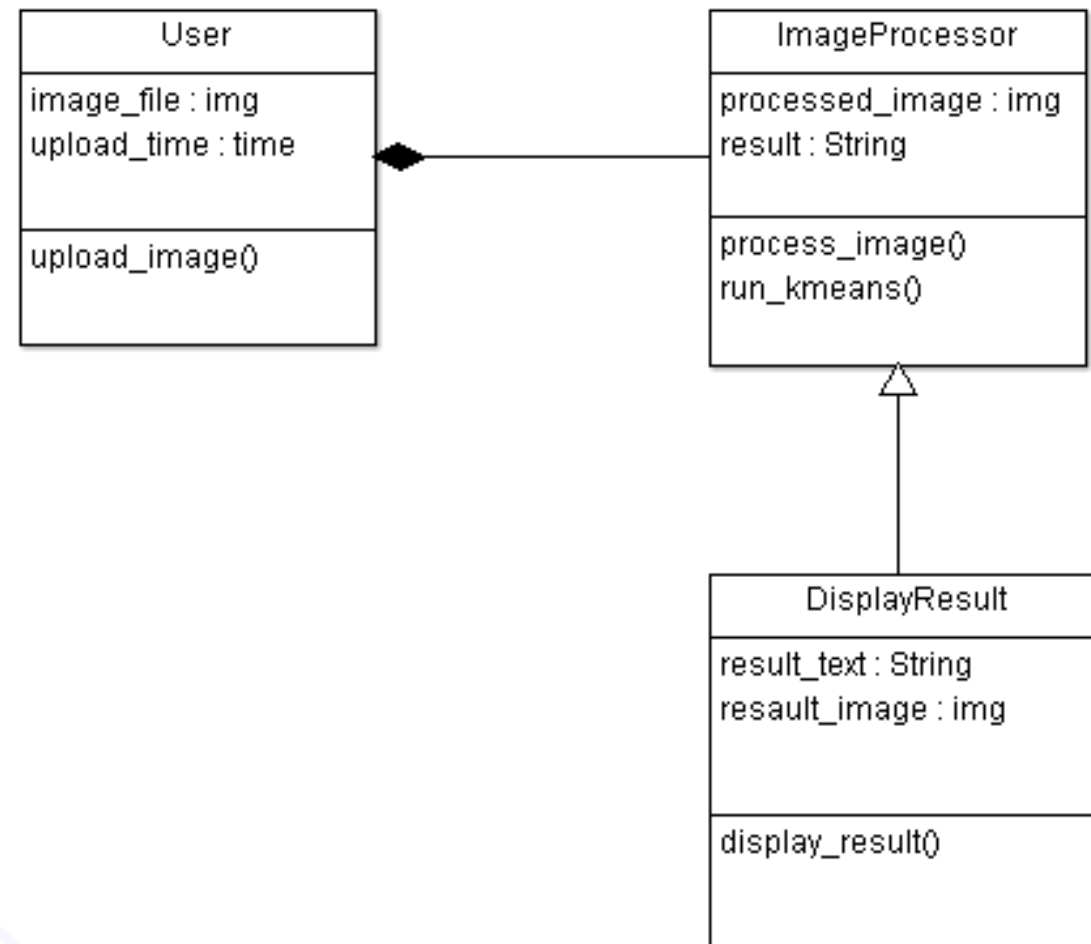
UML DIAGRAMS



USECASE DIAGRAM



UML DIAGRAMS

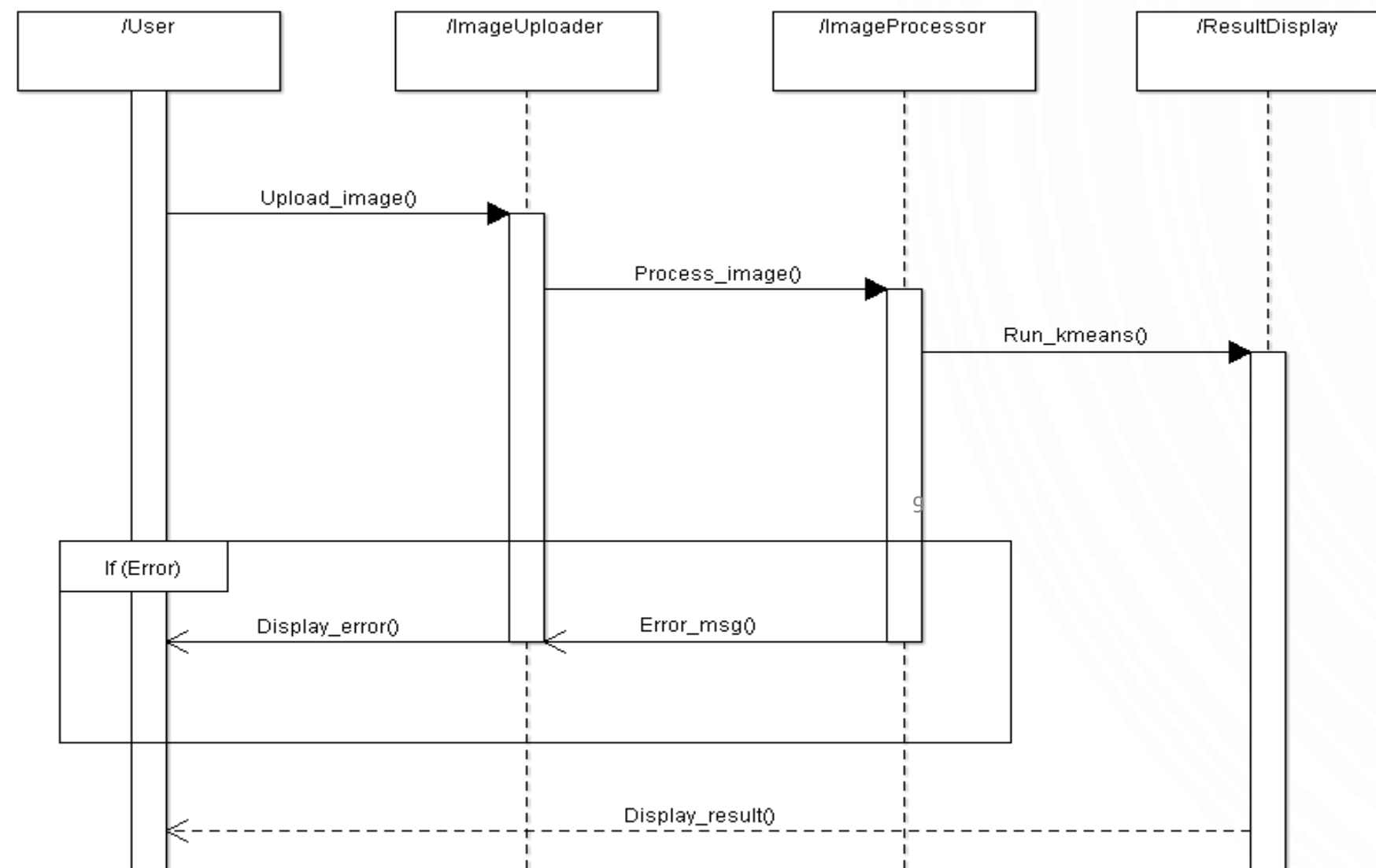


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CLASS DIAGRAM



UML DIAGRAMS

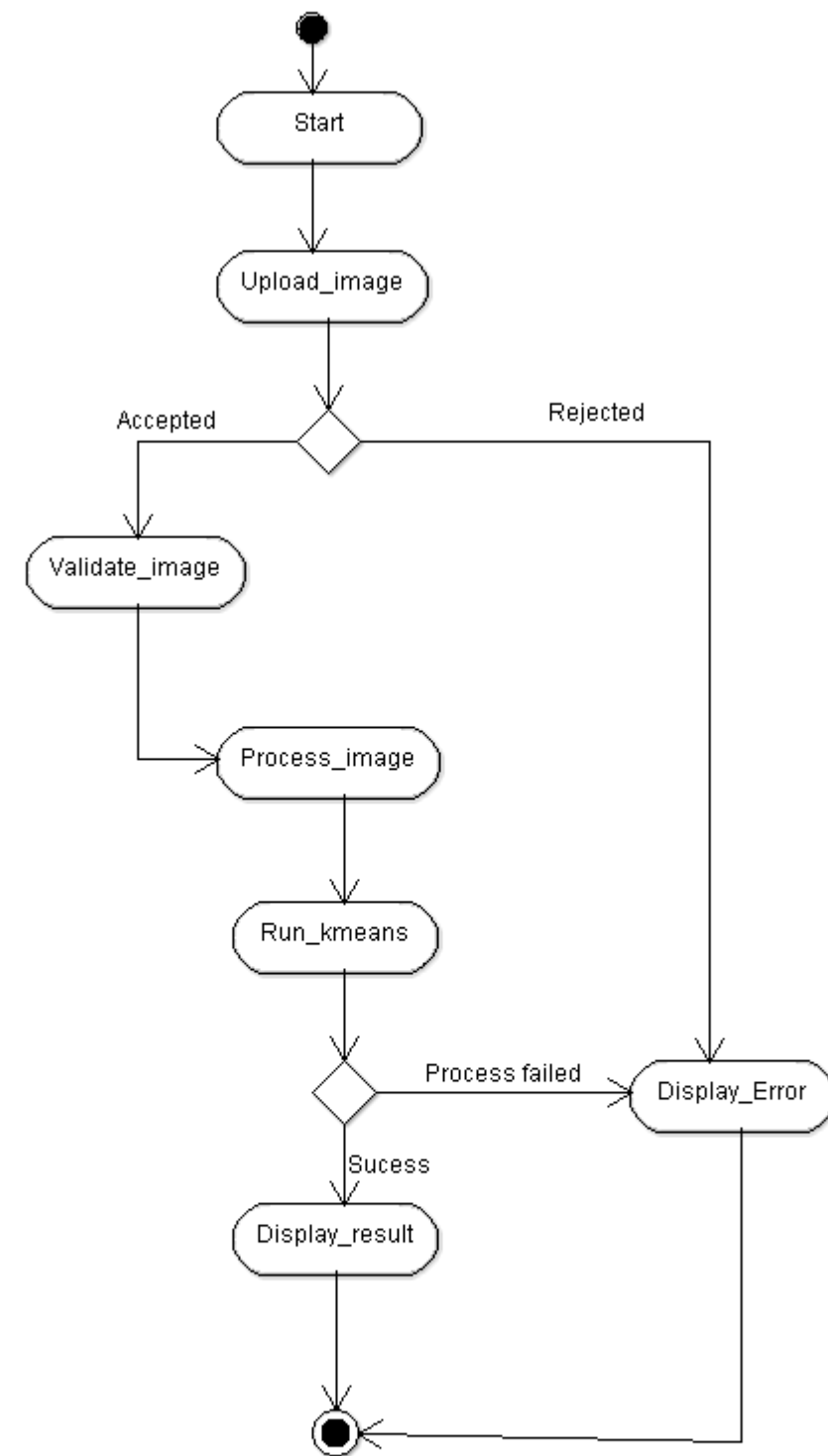


SEQUENCE DIAGRAM



UML DIAGRAMS

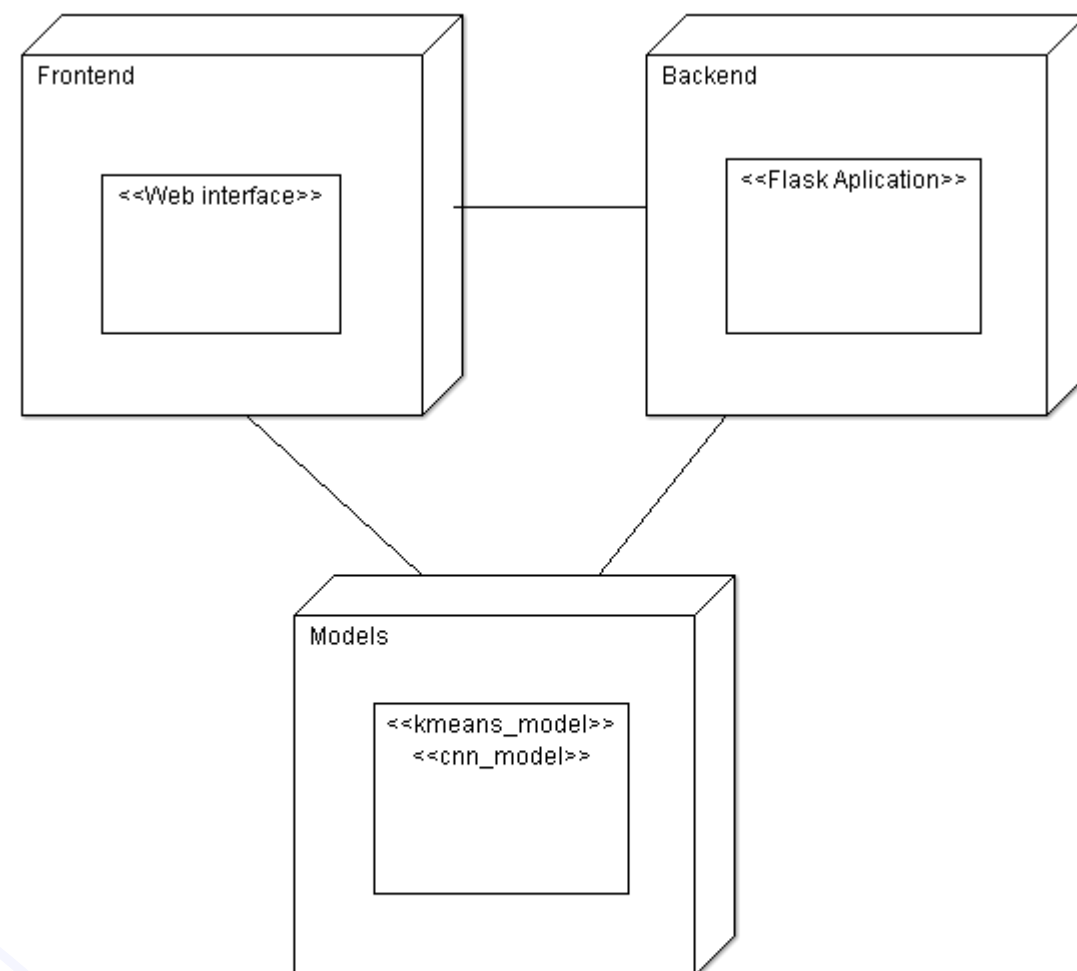
ACTIVITY DIAGRAM



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UML DIAGRAMS

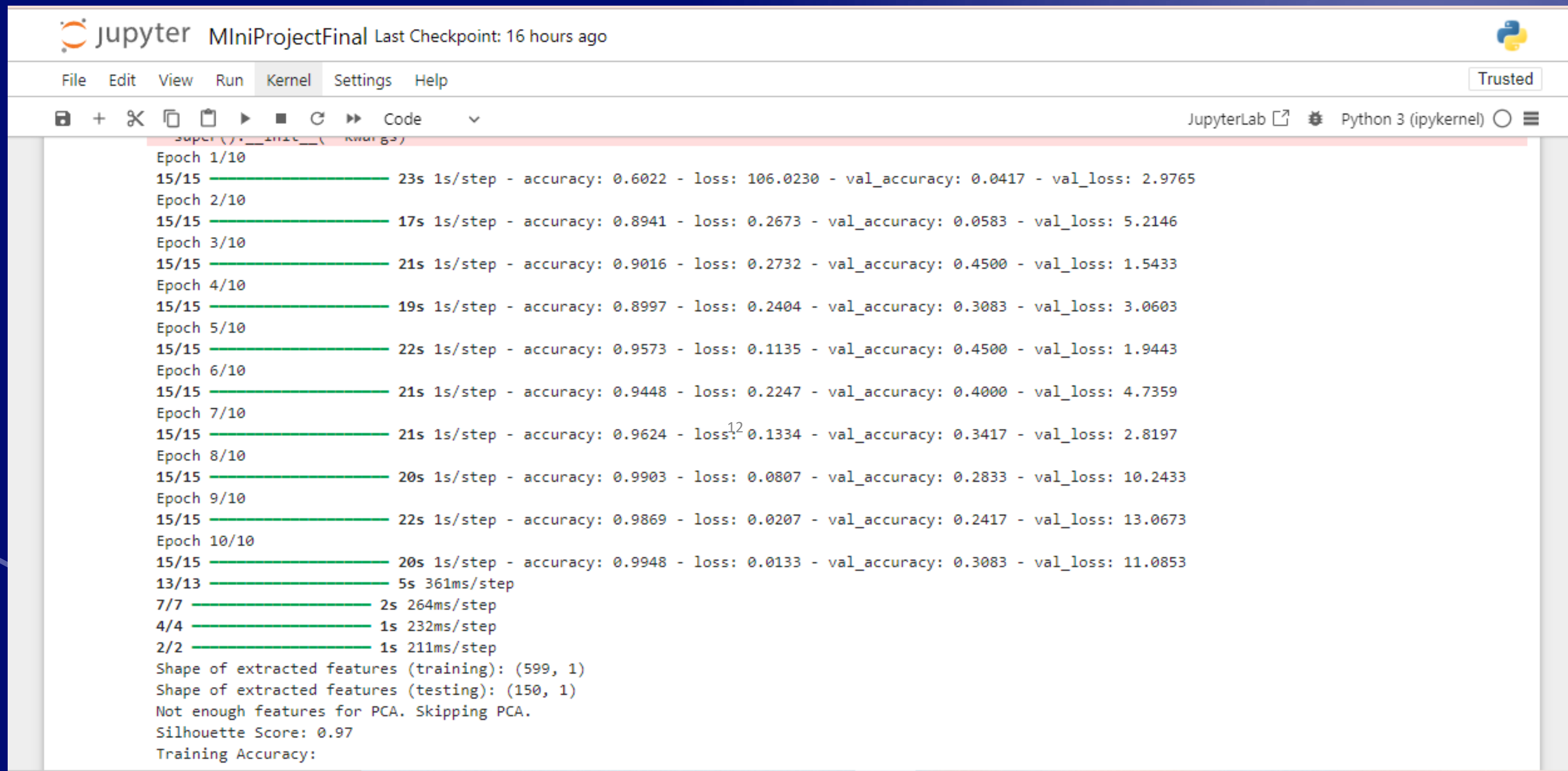


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COMPONENT DIAGRAM



TRAINING EPOCHS

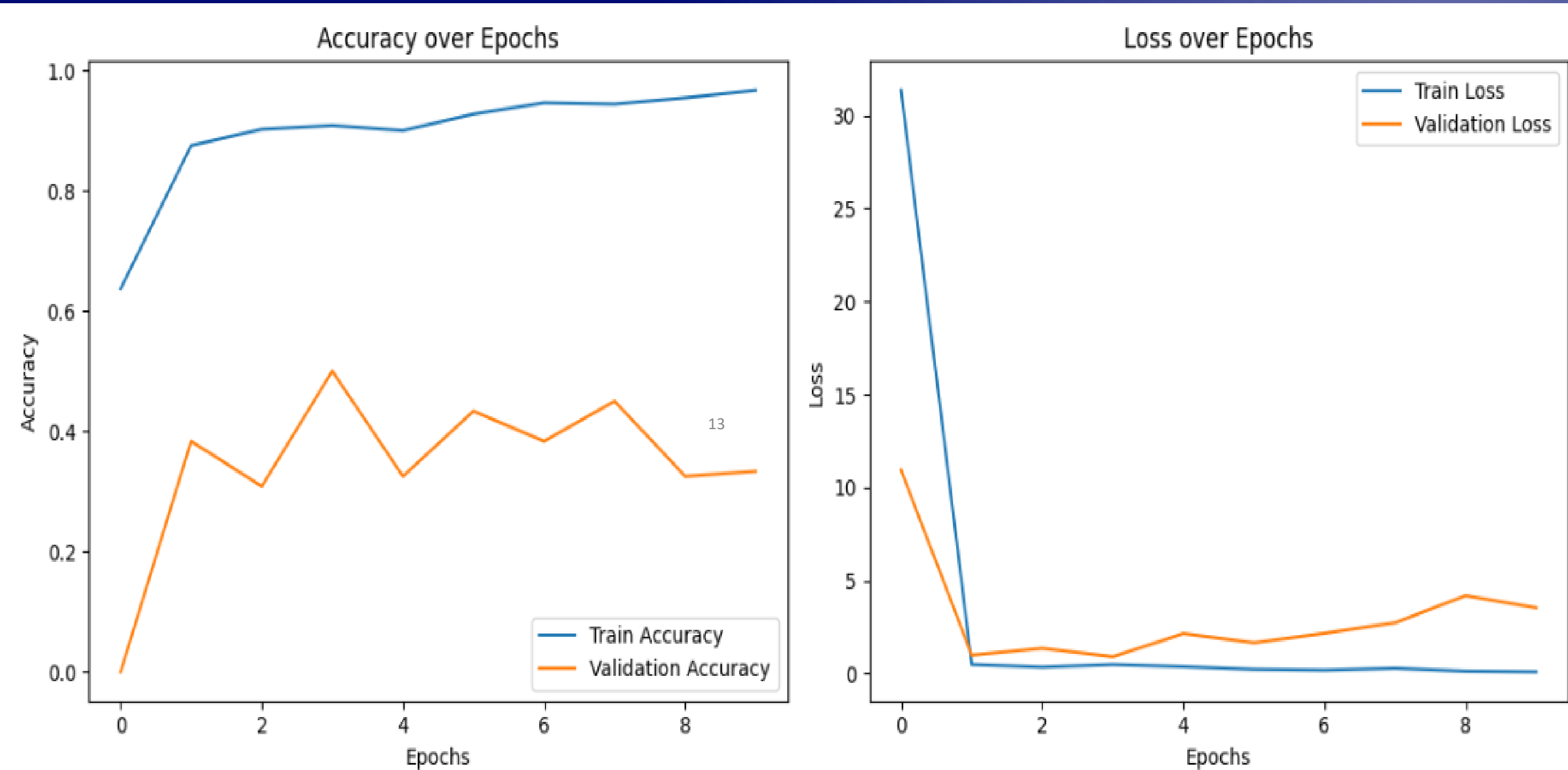


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jupyter MIniProjectFinal Last Checkpoint: 16 hours ago
File Edit View Run Kernel Settings Help Trusted
JupyterLab Python 3 (ipykernel)

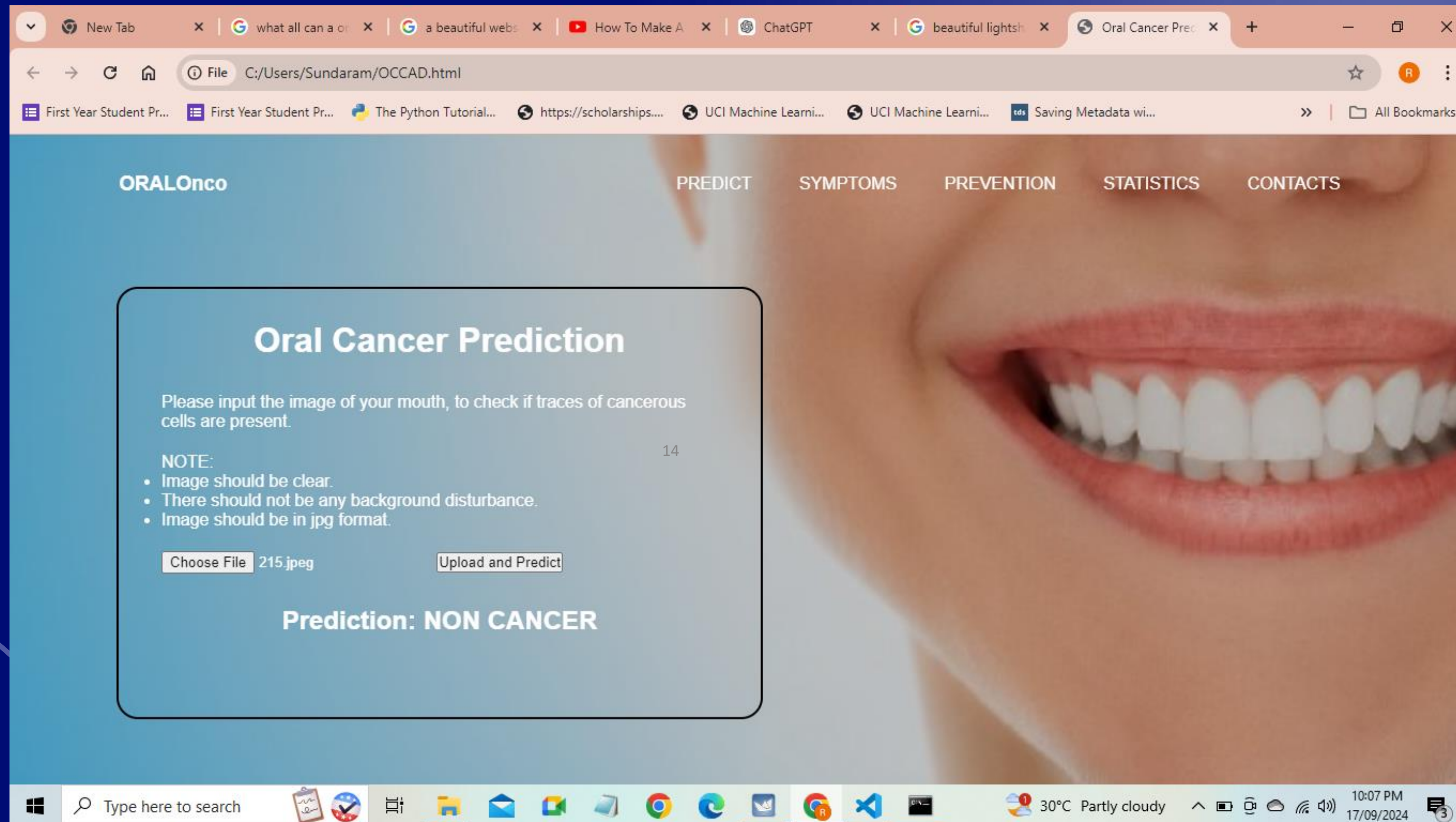
Epoch 1/10
15/15 ————— 23s 1s/step - accuracy: 0.6022 - loss: 106.0230 - val_accuracy: 0.0417 - val_loss: 2.9765
Epoch 2/10
15/15 ————— 17s 1s/step - accuracy: 0.8941 - loss: 0.2673 - val_accuracy: 0.0583 - val_loss: 5.2146
Epoch 3/10
15/15 ————— 21s 1s/step - accuracy: 0.9016 - loss: 0.2732 - val_accuracy: 0.4500 - val_loss: 1.5433
Epoch 4/10
15/15 ————— 19s 1s/step - accuracy: 0.8997 - loss: 0.2404 - val_accuracy: 0.3083 - val_loss: 3.0603
Epoch 5/10
15/15 ————— 22s 1s/step - accuracy: 0.9573 - loss: 0.1135 - val_accuracy: 0.4500 - val_loss: 1.9443
Epoch 6/10
15/15 ————— 21s 1s/step - accuracy: 0.9448 - loss: 0.2247 - val_accuracy: 0.4000 - val_loss: 4.7359
Epoch 7/10
15/15 ————— 21s 1s/step - accuracy: 0.9624 - loss: 0.1334 - val_accuracy: 0.3417 - val_loss: 2.8197
Epoch 8/10
15/15 ————— 20s 1s/step - accuracy: 0.9903 - loss: 0.0807 - val_accuracy: 0.2833 - val_loss: 10.2433
Epoch 9/10
15/15 ————— 22s 1s/step - accuracy: 0.9869 - loss: 0.0207 - val_accuracy: 0.2417 - val_loss: 13.0673
Epoch 10/10
15/15 ————— 20s 1s/step - accuracy: 0.9948 - loss: 0.0133 - val_accuracy: 0.3083 - val_loss: 11.0853
13/13 ————— 5s 361ms/step
7/7 ————— 2s 264ms/step
4/4 ————— 1s 232ms/step
2/2 ————— 1s 211ms/step
Shape of extracted features (training): (599, 1)
Shape of extracted features (testing): (150, 1)
Not enough features for PCA. Skipping PCA.
Silhouette Score: 0.97
Training Accuracy:
```



ACCURACY AND LOSS GRAPH



OUTPUT SCREEN



THANK
YOU

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