MACHINE LEARNING APPROACH TO DETECT & ANNOTATE EYE DISEASES USING RETINAL IMAGES

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Status Document

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1. Project progress

1.1 Datasets

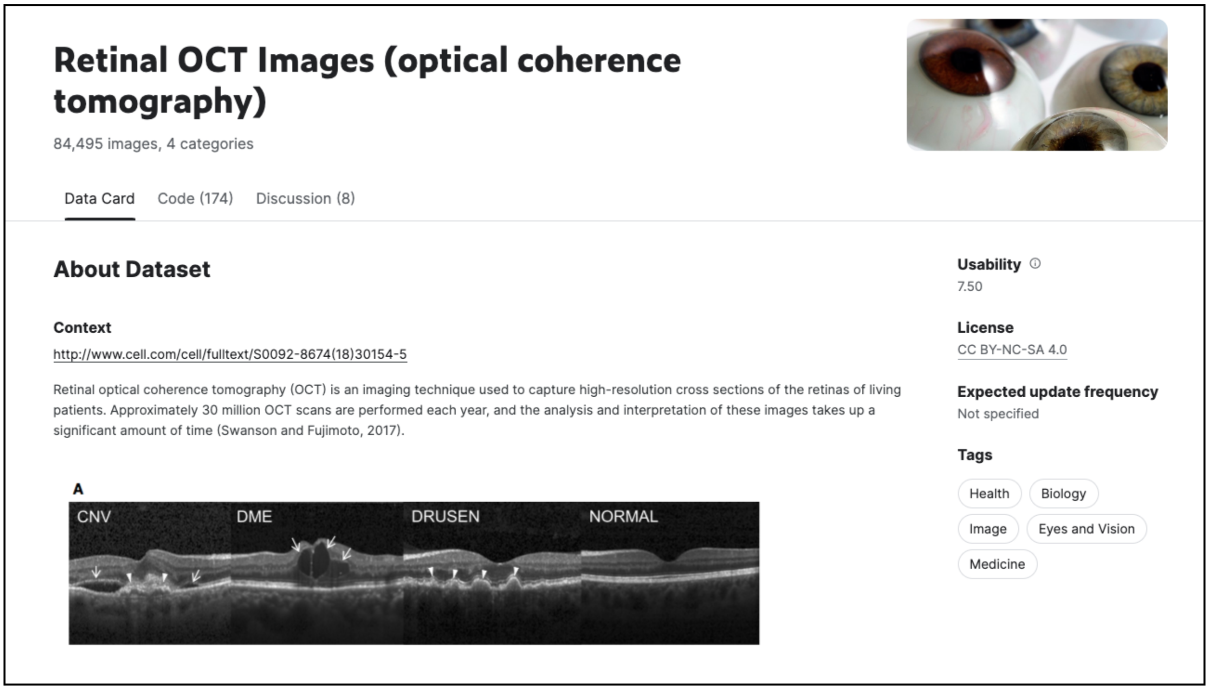


Figure 01: Kaggle Dataset

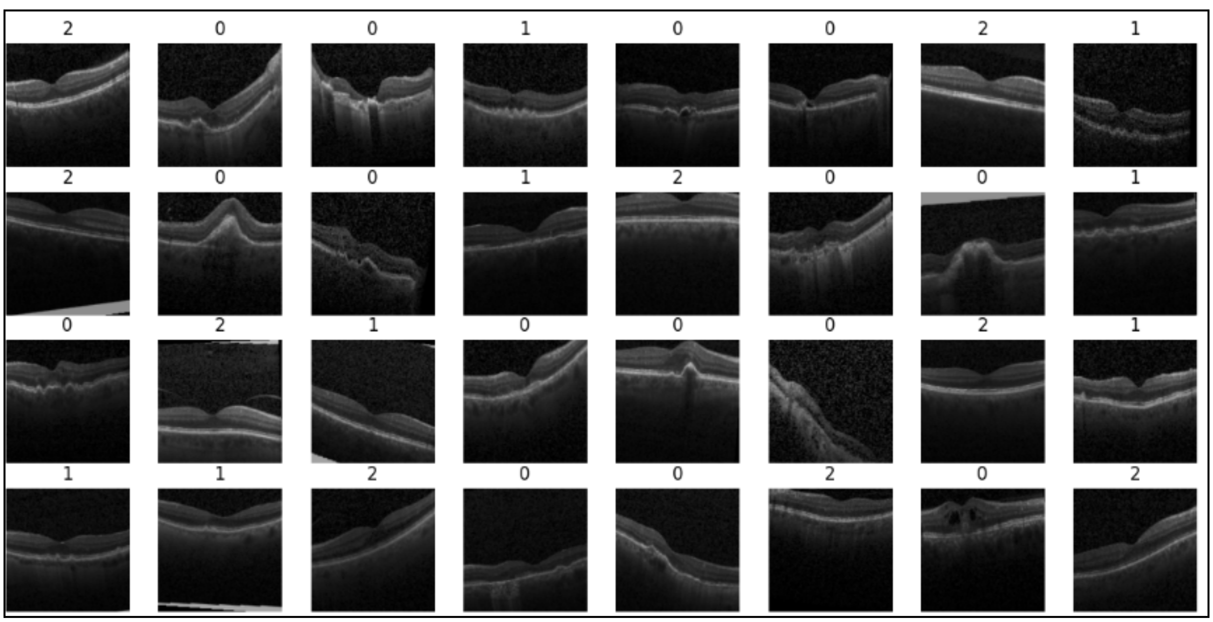
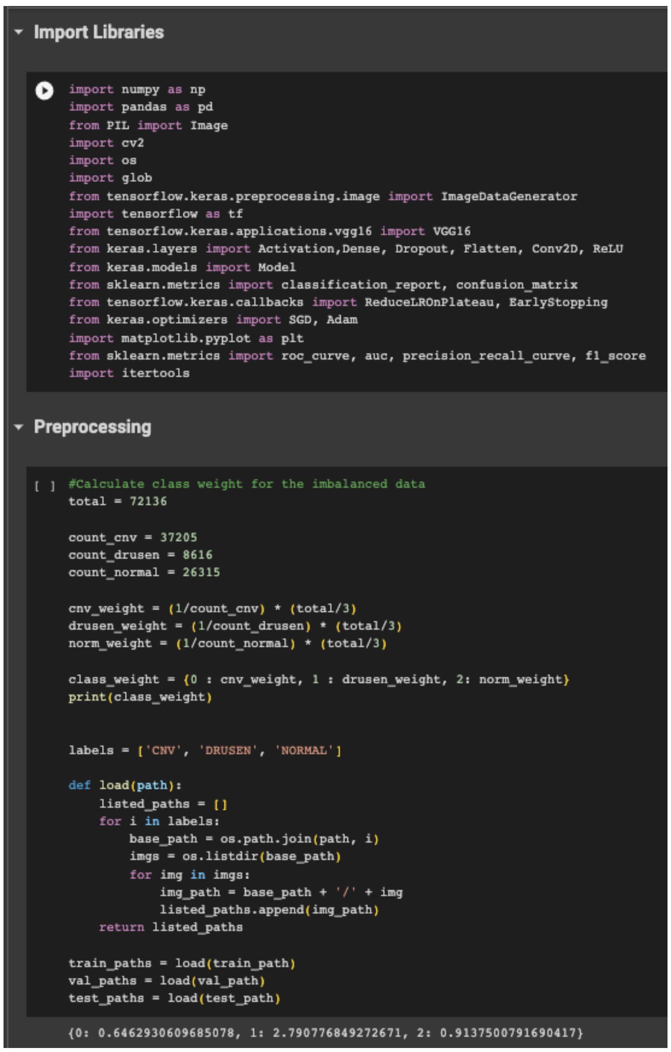


Figure 02: Sample Data

1.2 Age-Related Macular Degeneration Classification Model

This research aimed to develop a machine-learning model for classifying dry and wet age-related macular degeneration (AMD) from OCT images. The dataset consisted of 72,136 scans categorized into three classes: choroidal neovascularization (CNV), Drusen, and Normal retina. The images were processed to a standardized size of 150x150 pixels and normalized to improve consistency and quality. Data augmentation techniques were applied to increase the diversity of the dataset. The model architecture was based on the VGG16 model, with customized layers for AMD classification. The model was trained using the Adam optimizer and evaluated using accuracy, precision, recall, and F1-score metrics. Comparative analysis and interpretability techniques, such as activation maps, were used to assess the model's performance and understand its decision-making process.



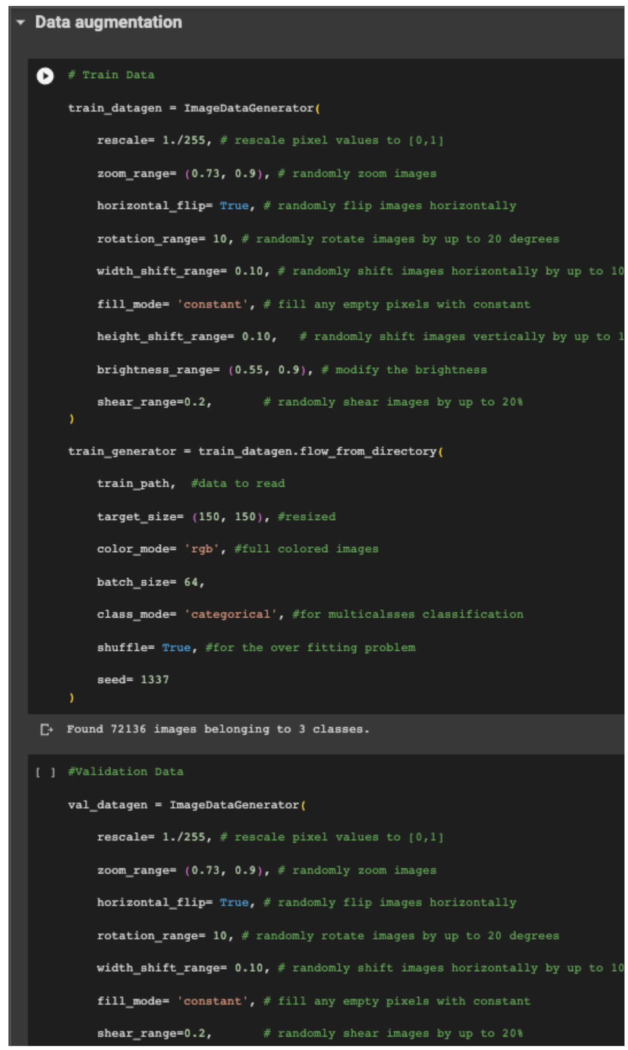
Import Libraries

```
import numpy as np
import pandas as pd
from PIL import Image
import cv2
import os
import glob
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import tensorflow as tf
from tensorflow.keras.applications.vgg16 import VGG16
from keras.layers import Activation,Dense, Dropout, Flatten, Conv2D, ReLU
from keras.models import Model
from sklearn.metrics import classification_report, confusion_matrix
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
from keras.optimizers import SGD, Adam
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc, precision_recall_curve, f1_score
import itertools
```

Preprocessing

```
#Calculate class weight for the imbalanced data
total = 72136

count_cnv = 37205
count_drusen = 8616
count_normal = 26315

cnv_weight = (1/count_cnv) * (total/3)
drusen_weight = (1/count_drusen) * (total/3)
norm_weight = (1/count_normal) * (total/3)

class_weight = {0 : cnv_weight, 1 : drusen_weight, 2: norm_weight}
print(class_weight)


labels = ['CNV', 'DRUSEN', 'NORMAL']

def load(path):
    listed_paths = []
    for i in labels:
        base_path = os.path.join(path, i)
        imgs = os.listdir(base_path)
        for img in imgs:
            img_path = base_path + '/' + img
            listed_paths.append(img_path)
    return listed_paths

train_paths = load(train_path)
val_paths = load(val_path)
test_paths = load(test_path)

{0: 0.6462930609685078, 1: 2.790776849272671, 2: 0.9137500791690417}
```

Figure 03: AMD Classification Model Implementation



Data augmentation

```
# Train Data

train_datagen = ImageDataGenerator(

    rescale= 1./255, # rescale pixel values to [0,1]

    zoom_range= (0.73, 0.9), # randomly zoom images

    horizontal_flip= True, # randomly flip images horizontally

    rotation_range= 10, # randomly rotate images by up to 20 degrees

    width_shift_range= 0.10, # randomly shift images horizontally by up to 10

    fill_mode= 'constant', # fill any empty pixels with constant

    height_shift_range= 0.10,   # randomly shift images vertically by up to 1

    brightness_range= (0.55, 0.9), # modify the brightness

    shear_range=0.2,       # randomly shear images by up to 20%
)

train_generator = train_datagen.flow_from_directory(

    train_path,  #data to read

    target_size= (150, 150), #resized

    color_mode= 'rgb', #full colored images

    batch_size= 64,

    class_mode= 'categorical', #for multicalsses classification

    shuffle= True, #for the over fitting problem

    seed= 1337
)

Found 72136 images belonging to 3 classes.

#Validation Data

val_datagen = ImageDataGenerator(

    rescale= 1./255, # rescale pixel values to [0,1]

    zoom_range= (0.73, 0.9), # randomly zoom images

    horizontal_flip= True, # randomly flip images horizontally

    rotation_range= 10, # randomly rotate images by up to 20 degrees

    width_shift_range= 0.10, # randomly shift images horizontally by up to 10

    fill_mode= 'constant', # fill any empty pixels with constant

    shear_range=0.2,       # randomly shear images by up to 20%
```

Figure 04: AMD Classification Model Implementation

Build the Model VGG16

```python
# pre-trained VGG16 model

base_model = VGG16(weights='imagenet', include_top=False, input_shape=(150, 150, 3))
trainable_layers = len(base_model.layers[:-5])
for layer in base_model.layers[:trainable_layers]:
    layer.trainable = False # Freeze the weights of all layers except for the last 5
for layer in base_model.layers[trainable_layers:]:
    layer.trainable = True
```

```python
# Add new classification layers on top of the pre-trained layers
num_classes = 3  # cnv, drusen, and normal.
x = Flatten()(base_model.output)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x) # Add a dropout layer with a rate of 0.5
predictions = Dense(num_classes, activation='softmax')(x)
```

```python
# Create the final model
model_3 = Model(inputs=base_model.input, outputs=predictions)
# Compile the model with Adam optimizer
opt = Adam(lr=0.0001)
model_3.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
# Define the callbacks
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=3, min_lr=0.00001)
early_stop = EarlyStopping(monitor='val_loss', patience=5)
# Train the model
num_epochs = 20
history_3 = model_3.fit(train_generator,
                              epochs = num_epochs,
                              steps_per_epoch = 500,
                              validation_data = val_generator,
                              validation_steps = len(val_generator),
                              callbacks = [reduce_lr, early_stop])
```

```
Epoch 1/20
500/500 [==============================] - 348s 695ms/step - loss: 0.2179 - accuracy: 0.9230 - val_loss: 0.0513 - val_accuracy: 1.0000 - lr: 1.0000e-04
Epoch 2/20
500/500 [==============================] - 341s 682ms/step - loss: 0.1854 - accuracy: 0.9347 - val_loss: 0.0311 - val_accuracy: 1.0000 - lr: 1.0000e-04
Epoch 3/20
500/500 [==============================] - 338s 676ms/step - loss: 0.1743 - accuracy: 0.9397 - val_loss: 0.0548 - val_accuracy: 0.9583 - lr: 1.0000e-04
Epoch 4/20
500/500 [==============================] - 337s 675ms/step - loss: 0.1637 - accuracy: 0.9427 - val_loss: 0.0370 - val_accuracy: 1.0000 - lr: 1.0000e-04
Epoch 5/20
500/500 [==============================] - 328s 656ms/step - loss: 0.1526 - accuracy: 0.9471 - val_loss: 0.0443 - val_accuracy: 1.0000 - lr: 1.0000e-04
Epoch 6/20
500/500 [==============================] - 326s 652ms/step - loss: 0.1303 - accuracy: 0.9521 - val_loss: 0.0215 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 7/20
500/500 [==============================] - 326s 652ms/step - loss: 0.1302 - accuracy: 0.9541 - val_loss: 0.0243 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 8/20
500/500 [==============================] - 325s 649ms/step - loss: 0.1233 - accuracy: 0.9560 - val_loss: 0.0487 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 9/20
500/500 [==============================] - 324s 648ms/step - loss: 0.1222 - accuracy: 0.9577 - val_loss: 0.0204 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 10/20
500/500 [==============================] - 323s 646ms/step - loss: 0.1196 - accuracy: 0.9581 - val_loss: 0.0197 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 11/20
500/500 [==============================] - 325s 650ms/step - loss: 0.1206 - accuracy: 0.9584 - val_loss: 0.0202 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 12/20
500/500 [==============================] - 323s 645ms/step - loss: 0.1158 - accuracy: 0.9584 - val_loss: 0.0372 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 13/20
500/500 [==============================] - 364s 727ms/step - loss: 0.1117 - accuracy: 0.9610 - val_loss: 0.0197 - val_accuracy: 1.0000 - lr: 2.0000e-05
Epoch 14/20
500/500 [==============================] - 330s 659ms/step - loss: 0.1091 - accuracy: 0.9619 - val_loss: 0.0163 - val_accuracy: 1.0000 - lr: 1.0000e-05
```

Figure 05: AMD Classification Model Implementation

2. Project View

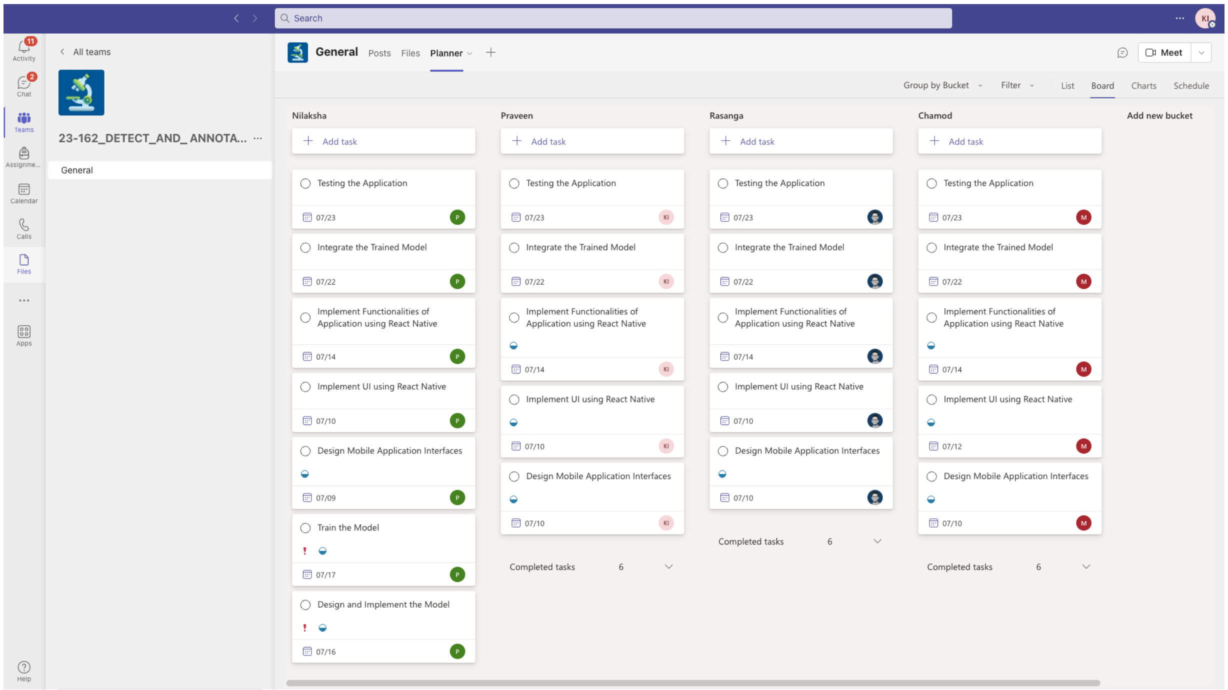


Figure 06: Planner – Board View

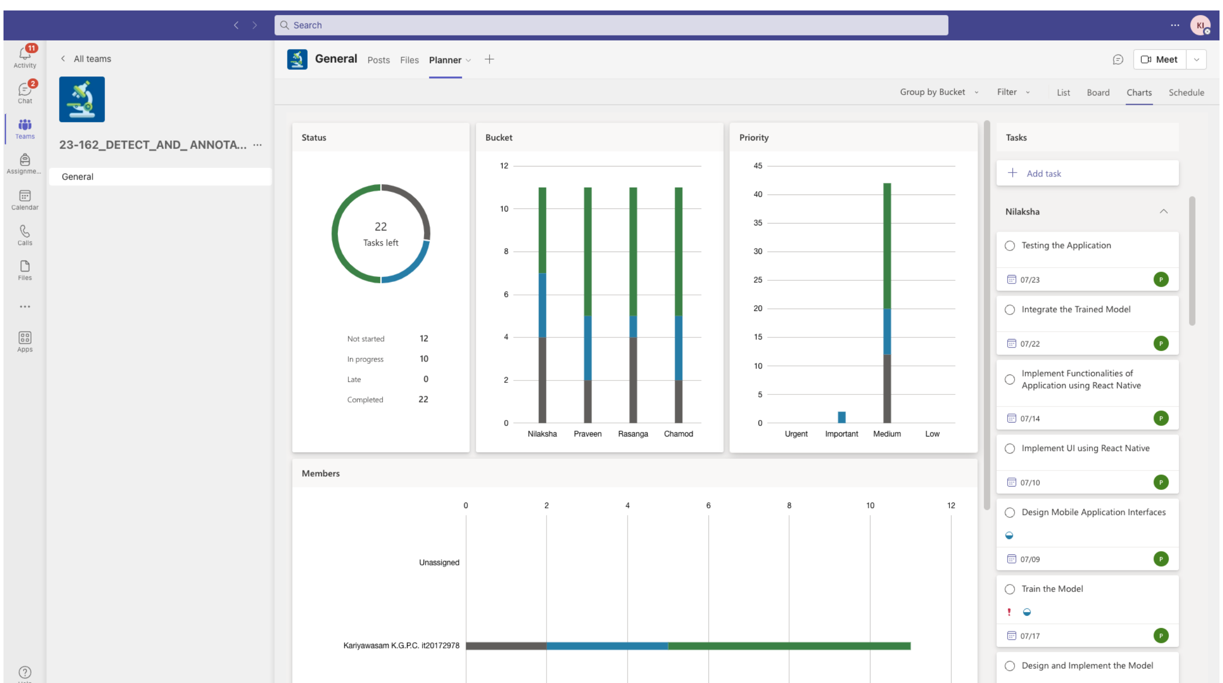


Figure 07: Planner – Chart View

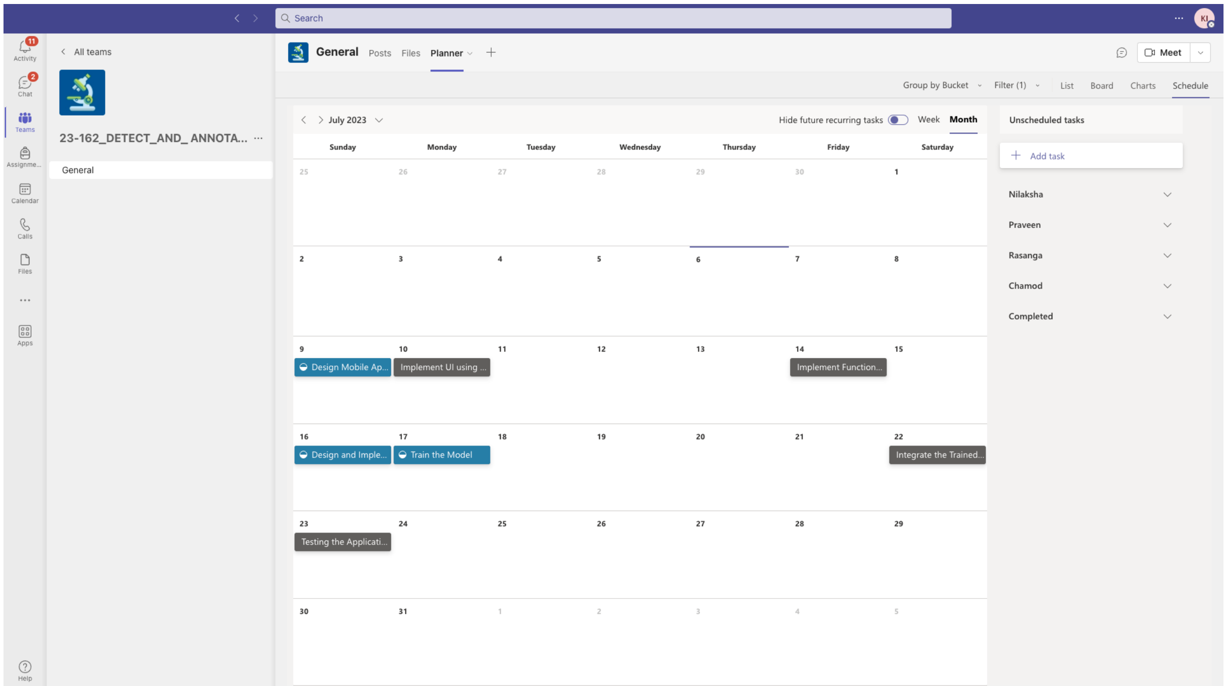


Figure 08: Planner – Schedule View

3. Updated Gantt chart

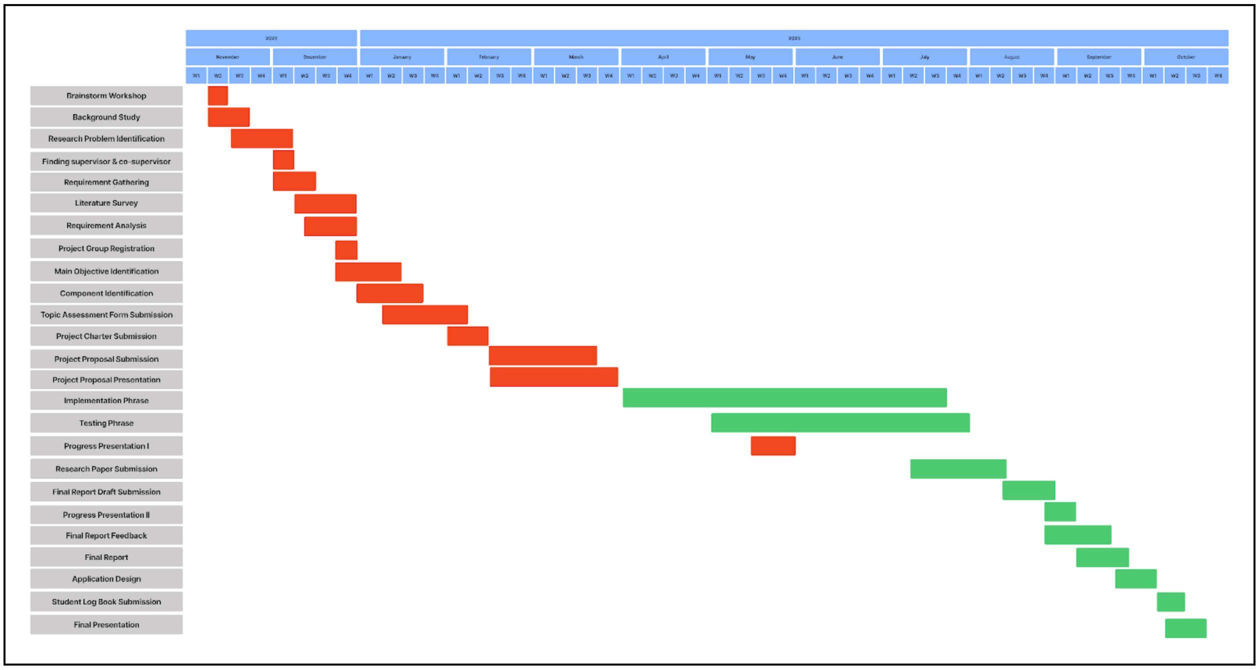


Figure 09: Gantt Chart

4. Screenshots of chats and calls of MS Teams

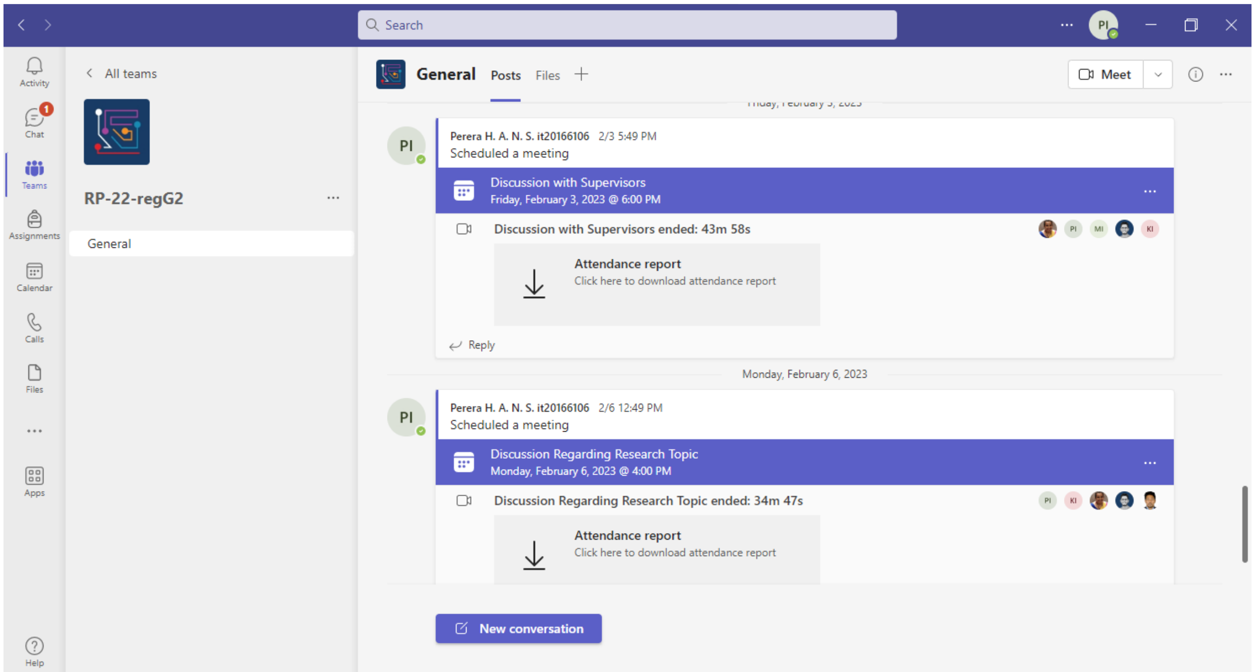


Figure 10: Screenshots of MS Teams Chats

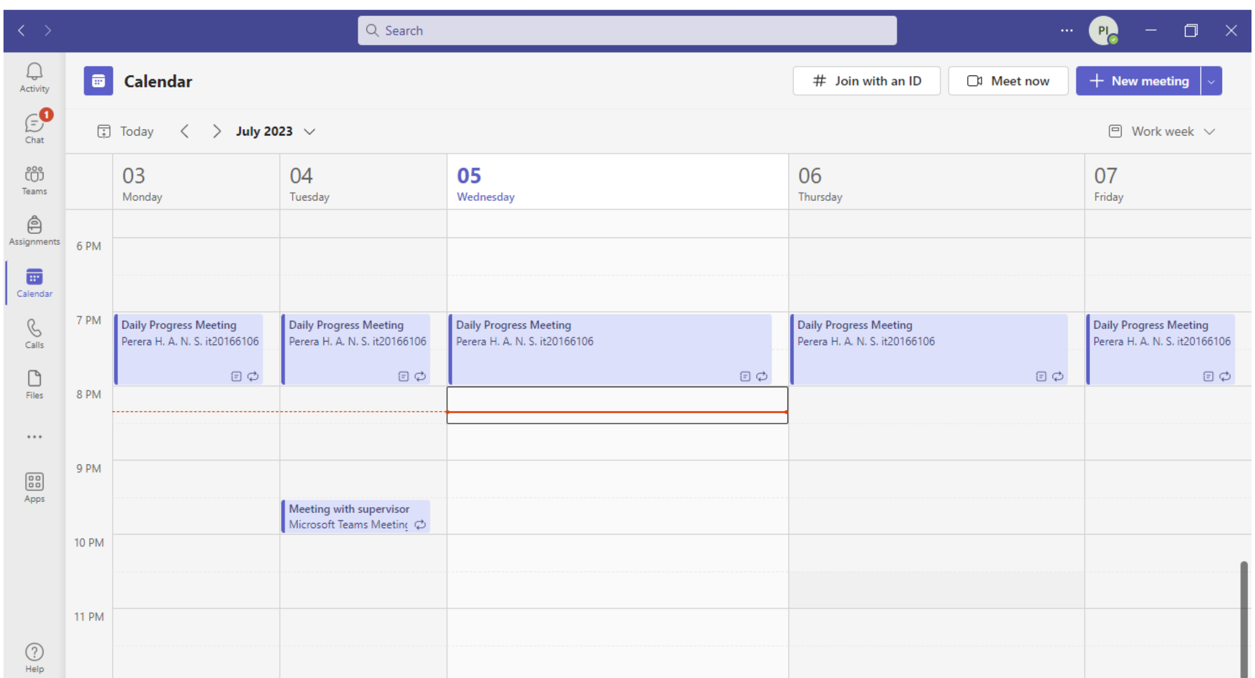


Figure 11: Screenshots of MS Teams Calendar Schedule

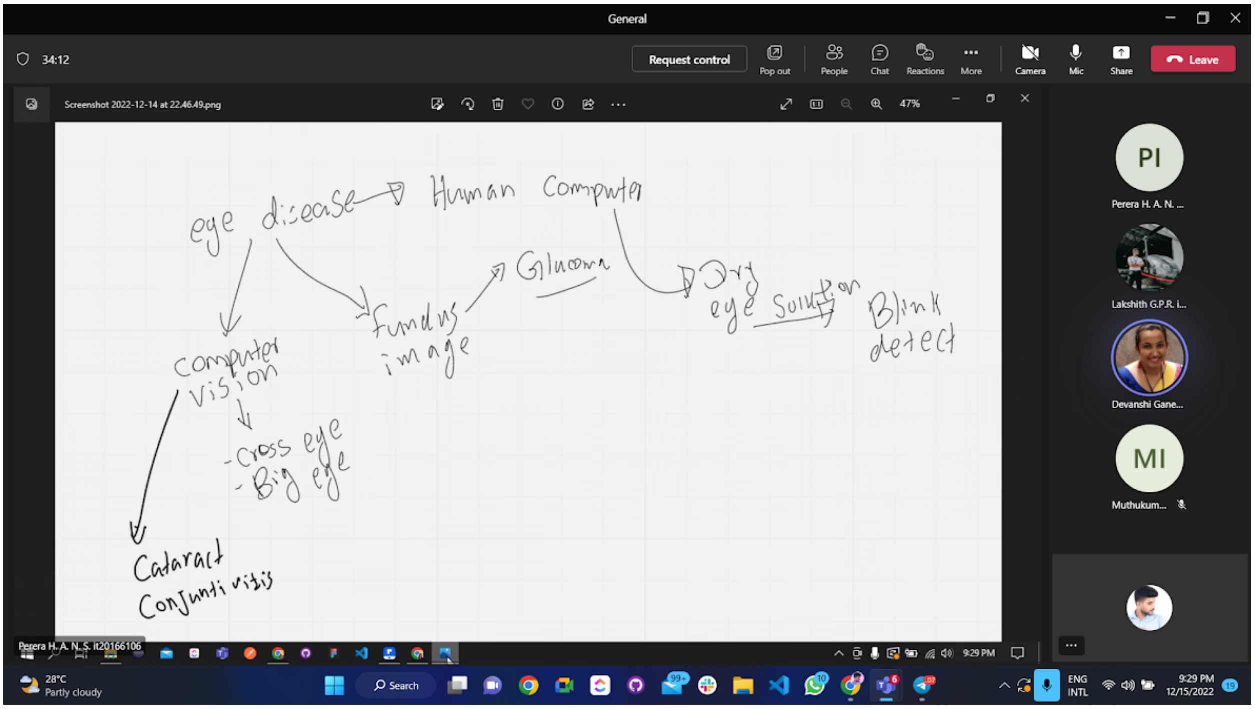


Figure 12: Screenshots of MS Teams Meetings