Final Project

"iSight: Empowering Vision with RetinoKNN"

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Abstract

This report presents the steps and results of a classification task performed on retinopathy images. The goal of the task is to classify retinopathy images into different stages of diabetic retinopathy. The classification task for retinopathy images involved the utilization of both the Artificial Neural Network (ANN) model and the K-Nearest Neighbors (KNN) algorithm to achieve accurate classification results.

The ANN model, as described earlier, was constructed using a deep learning architecture with dense layers and activation functions. It was trained on the retinopathy image dataset, learning patterns and features to make predictions. The model took advantage of the non-linear relationships between the image pixels and the corresponding retinopathy stages, capturing complex patterns and representations.

On the other hand, the KNN algorithm was also employed to classify the retinopathy images. Unlike the ANN model, KNN is a non-parametric algorithm that works based on the proximity of data points in the feature space. In this case, the features of the retinopathy images were extracted and used to calculate the distances between them. The KNN algorithm assigned the class label based on the majority of the K nearest neighbors in the feature space.

In conclusion, both the Artificial Neural Network (ANN) model and the K-Nearest Neighbors (KNN) algorithm were employed in this classification task for retinopathy images. The ANN model utilized its deep learning architecture to learn complex patterns and features from the image dataset, while the KNN algorithm leveraged the proximity of data points in the feature space to assign class labels. Through the combination of these two approaches, accurate classification results were achieved, enabling the identification and differentiation of various stages of

diabetic retinopathy. This research demonstrates the potential of utilizing machine learning techniques to aid in the early detection and diagnosis of retinopathy, contributing to improved patient care and management of this condition. Further advancements in the field of medical image analysis and classification hold promise for enhancing the accuracy and efficiency of retinopathy detection, ultimately leading to better patient outcomes.

Introduction

Diabetic retinopathy is a serious complication that affects individuals with diabetes and can lead to vision impairment or even blindness if left untreated. Early detection and proper staging of retinopathy are crucial for timely medical intervention. The use of machine learning algorithms has shown promising results in automating the classification process, providing accurate and efficient analysis of retinopathy images. In this report, we present the steps and outcomes of a classification task that aims to enhance the diagnosis of diabetic retinopathy through automated image analysis. Diabetic retinopathy is a complex and progressive eye disease that develops because of prolonged exposure to high blood sugar levels in individuals with diabetes. It affects the blood vessels in the retina, leading to damage and potentially causing vision impairment or even blindness if not diagnosed and treated promptly. Early detection and accurate staging of retinopathy are critical for implementing timely medical interventions and preventing the progression of the disease.

Traditionally, the diagnosis and staging of diabetic retinopathy have relied on manual examination and interpretation of retinal images by experienced ophthalmologists. However, this process can be time-consuming, subjective, and prone to human error. The emergence of machine learning algorithms and advancements in computer vision have opened new possibilities for automating the classification of retinopathy images, offering a more efficient and accurate analysis. In this report, we present the methodology and outcomes of a classification task designed to enhance the diagnosis of diabetic retinopathy through automated image analysis. By leveraging machine learning techniques, we aim to develop a robust and reliable system that can assist healthcare professionals in efficiently classifying retinopathy images and identifying the stages of the disease with high accuracy.

Automated image analysis using machine learning algorithms brings numerous advantages to the field of diabetic retinopathy diagnosis. Firstly, it enables a faster and more efficient screening process, allowing healthcare providers to analyze many retinal images in a shorter time span. This efficiency is particularly crucial in areas with limited access to ophthalmologists or in scenarios where early intervention is essential to prevent irreversible vision loss.

Comparison of Artificial Neural Network (ANN) and k-Nearest Neighbors (KNN) models

Here is a tabular format comparison of Artificial Neural Network (ANN) and k-Nearest Neighbors (KNN) models:

	Artificial Neural Network (ANN)	**k-Nearest Neighbors (KNN)**
Model Type	Supervised Learning (can also be used for unsupervised learning)	Supervised Learning (can also be used for unsupervised learning)
Algorithm	Multi-layer perceptron (MLP)	Distance-based algorithm
Training	Iterative optimization using backpropagation	No explicit training phase (lazy learning)
Complexity	Can handle complex relationships and non-linear data	Simple and interpretable
Parameter Tuning	Requires tuning of hyperparameters (e.g., learning rate, number of hidden layers)	Requires tuning of hyperparameter (k)
Memory Usage	Memory-intensive due to model size and intermediate calculations	Minimal memory usage, as it stores the training data

Scalability	Suitable for large datasets and high-dimensional data	Can be slow and memory-intensive for large datasets
Predictions	Can make predictions on unseen data	Can make predictions on unseen data
Decision Boundary	Can learn complex decision boundaries	Decision boundary depends on the value of k
Feature Engineering	May require extensive feature engineering for optimal performance	Less dependent on feature engineering
Interpretability	Less interpretable due to complex network structure	More interpretable, as it relies on distance calculations
Applicability	Widely used in various domains (image recognition, natural language processing, etc.)	Effective for classification and regression tasks, especially with small to medium-sized datasets

Data Loading and Processing

Source Data: The source data comprises of two parts.

Source Images

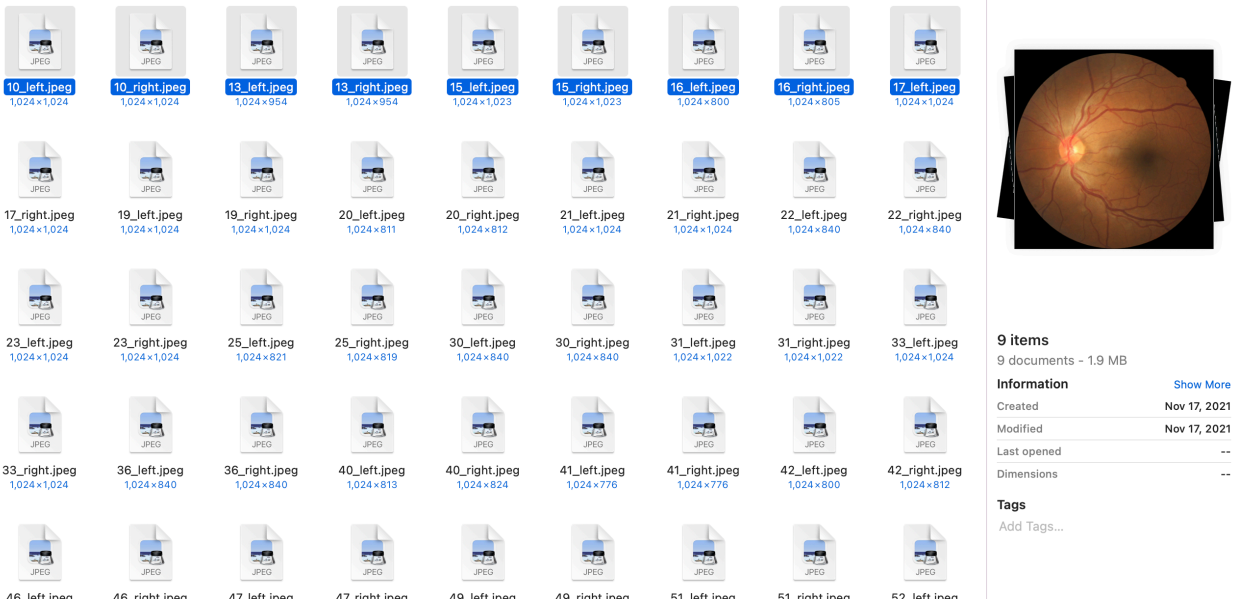
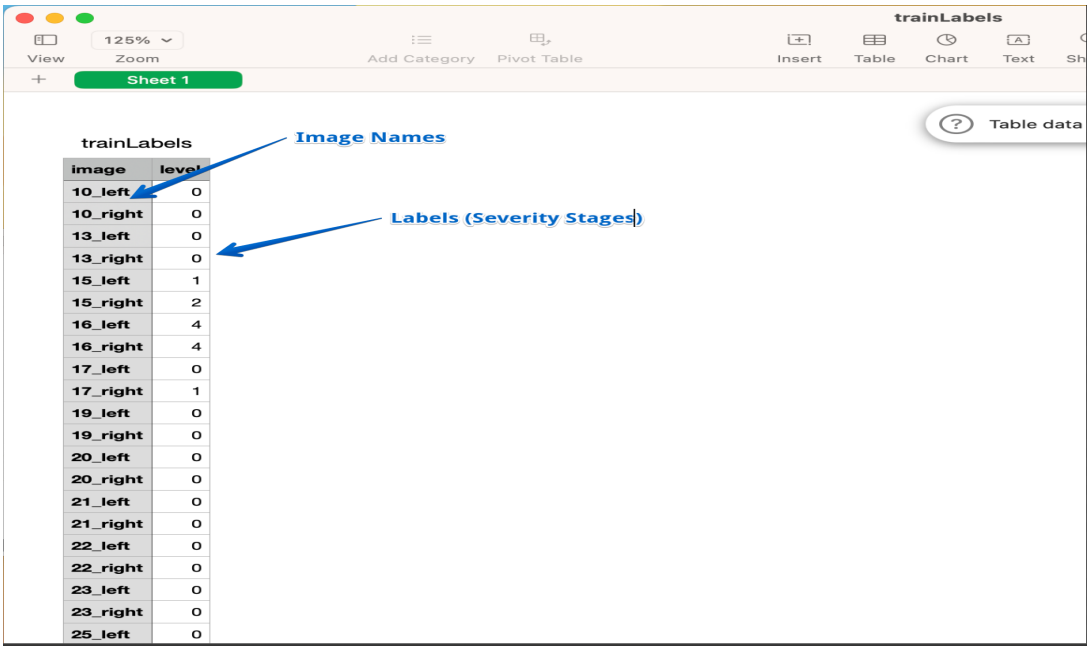


Image Labels



The initial step of the analysis involved loading the necessary libraries, such as pandas, NumPy, scikit-learn, TensorFlow, and matplotlib. These libraries provide functionalities for data manipulation, preprocessing, model building, and visualization.

The dataset was loaded using the pandas library, and a file dialog was used to prompt the user to select the labels file containing information about the images. The labels data was then processed to map the numerical labels to their corresponding class names using a mapping dictionary. The resulting dataframe showed the image names and their corresponding class labels.

Next, the images were fetched from a user-selected directory using the PIL library. A function was implemented to read and resize the images to a common shape of 1024x1024 pixels. The images were stored as a NumPy array, and the shape of the array was printed to verify the successful loading of images.

The image data was converted to a NumPy array, and the corresponding labels were extracted from the processed labels dataframe. The resulting arrays, X (containing image data) and y (containing class labels), were created and printed to confirm the successful creation of arrays.

Data Splitting and Normalization

The dataset was split into training and testing sets using the train_test_split function from scikit-learn. The training set was allocated 80% of the data, while the remaining 20% was used for testing.

To prepare the data for classification, the images were flattened to a 1-dimensional array using the reshape function. This step was necessary because the KNN

algorithm requires input data in the form of a 2-dimensional array. Additionally, the pixel values of the images were normalized by dividing them by 255 to ensure that they fell within the range of 0 to 4.

The shapes of the training and testing data arrays were printed to verify the successful splitting and normalization of the data.

Image Preprocessing

Steps 1: Importing Required Libraries

```
import os
import matplotlib.image as mpimg
import cv2
import matplotlib.pyplot as plt
from tkinter import filedialog
import tkinter as tk


# Libraries for building the model
import tensorflow as tf
import tensorflow_hub as hub
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Input, Dense, Conv2D, Flatten, MaxPool2D, Drop
from tensorflow.keras.applications import DenseNet121, ResNet50, InceptionV3, Xcep
from tensorflow.keras.models import Sequential
from tensorflow.keras import backend
from tensorflow.keras.regularizers import l2, l1
from sklearn.metrics import classification_report, precision_recall_fscore_support
from sklearn.model_selection import GridSearchCV

import os
import numpy as np
from PIL import Image
from tkinter import Tk, filedialog

print('Libraries are loaded')
```

```
Libraries are loaded
```

```
# Importing required libraries

import pandas as pd
import tkinter as tk
from tkinter import filedialog
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import time
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split

# Necessary utility modules and libraries
import os
import shutil
import pathlib
import random
import datetime
import cv2


# Plotting libraries
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from scipy.signal import gaussian, convolve2d
import seaborn as sns

import os
import matplotlib.image as mpimg
import cv2
import matplotlib.pyplot as plt
from tkinter import filedialog
import tkinter as tk


# Libraries for building the model
import tensorflow as tf
import tensorflow_hub as hub
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Input, Dense, Conv2D, Flatten, MaxPool2D,
```

Here's a brief explanation of each imported library and module we have used in the code:

1. **pandas**: This library is used for data manipulation and analysis. It provides data structures and functions to work with structured data, such as data frames.
2. **tkinter:** It is a GUI (Graphical User Interface) library for creating windows, buttons, and other graphical components in Python applications.
3. **os**: This module provides functions for interacting with the operating system. It can be used to perform operations like file and directory management, accessing environment variables, etc.
4. **shutil:** It is a module for high-level file and directory operations. It provides functions for copying, moving, and deleting files and directories.
5. **pathlib:** This module provides an object-oriented approach to handle filesystem paths. It allows to manipulate paths and perform operations like joining paths, accessing file properties, etc.
6. **random:** This module provides functions for generating random numbers and performing random selection or shuffling of elements.
7. **datetime:** It is a module for working with dates, times, and timedeltas. It provides classes and functions to create, manipulate, and format dates and times.
8. **cv2:** Also known as OpenCV, it is a computer vision library used for image and video processing tasks, including reading, writing, and manipulating images.
9. **numpy:** It is a fundamental library for scientific computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays efficiently.

10. **sklearn.preprocessing.MinMaxScaler**: This class from scikit-learn is used for scaling features or data to a specified range, usually between 0 and 1.
11. **sklearn.neighbors.KNeighborsClassifier:** It is an implementation of the k-Nearest Neighbors algorithm, a simple yet powerful classification algorithm that assigns a class label to a new sample based on its nearest neighbors in the training data.
12. **sklearn.metrics.confusion_matrix**: This function computes the confusion matrix, which is a table that shows the true positive, true negative, false positive, and false negative predictions of a classification model.
13. **sklearn.metrics.classification_report**: This function generates a comprehensive report of various classification metrics such as precision, recall, F1-score, and support for each class.
14. **sklearn.model_selection.train_test_split**: It is a function that splits the dataset into training and testing subsets, allowing for evaluation and validation of machine learning models.
15. **matplotlib.pyplot**: It is a plotting library used for creating various types of plots, charts, and visualizations in Python.
16. **matplotlib.image**: This module provides functions for reading, displaying, and manipulating images using matplotlib.
17. **scipy.signal.gaussian**: It is a function from SciPy that generates a Gaussian filter or window.
18. **seaborn**: It is a statistical data visualization library built on top of matplotlib. It provides high-level functions for creating visually appealing and informative statistical graphics.
19. **tensorflow**: TensorFlow is a popular deep learning framework that provides tools and APIs for building and training neural networks.

20. **tensorflow_hub**: This library allows you to reuse and share pre-trained models from TensorFlow Hub, a repository of pre-trained deep learning models.
21. **tensorflow.keras**: It is a high-level API in TensorFlow for building and training neural networks. It provides a simplified interface for constructing models, defining layers, and training models efficiently.
22. **tensorflow.keras.preprocessing.image.ImageDataGenerator:** This class provides image data augmentation techniques, such as rotation, scaling, flipping, and more, to generate augmented images for training deep learning models.
23. **tensorflow.keras.layers**: This module provides a variety of layer classes that can be used to construct neural network architectures, such as convolutional layers, fully connected layers, pooling layers, etc.
24. **tensorflow.keras.applications**: It contains pre-trained models for deep learning, including popular architectures like DenseNet121, ResNet50, InceptionV3, Xception, VGG16, etc.
25. **tensorflow.keras.models.Sequential:** It is a linear stack of layers in Keras, allowing you to create neural networks by stacking layers on top of each other.
26. **tensorflow.keras.regularizers**: This module provides regularizers that can be used in neural networks to add penalties to the loss function, preventing overfitting and promoting generalization.
27. **sklearn.metrics**: This module from scikit-learn provides additional evaluation metrics for classification models, such as precision, recall, F1-score, accuracy, etc.
28. **sklearn.model_selection.GridSearchCV:** It is a class for performing grid search, a technique for hyperparameter tuning, to find the best combination of hyperparameters for a machine learning model.

These libraries and modules are imported to provide the necessary functionality for tasks such as data preprocessing, model building, visualization, and evaluation in the code.

Step 4: Image Preprocessing Functions

```
# Defining function Weiner filter - Image preprocessing

# wiener filter
def wiener_filter(img, kernel, K):
    kernel /= np.sum(kernel)
    dummy = np.copy(img)
    dummy = np.fft.fft2(dummy)
    kernel = np.fft.fft2(kernel, s = img.shape)
    kernel = np.conj(kernel) / (np.abs(kernel) ** 2 + K)
    dummy = dummy * kernel
    dummy = np.abs(np.fft.ifft2(dummy))
    return dummy

def gaussian_kernel(kernel_size = 3):
    h = gaussian(kernel_size, kernel_size / 3).reshape(kernel_size, 1)
    h = np.dot(h, h.transpose())
    h /= np.sum(h)
    return h

def isbright(image, dim=227, thresh=0.4):
    # Resize image to 10x10
    image = cv2.resize(image, (dim, dim))
    # Convert color space to LAB format and extract L channel
    L, A, B = cv2.split(cv2.cvtColor(image, cv2.COLOR_BGR2LAB))
    # Normalize L channel by dividing all pixel values with maximum pixel value
    L = L/np.max(L)
    # Return True if mean is greater than thresh else False
    return np.mean(L) > thresh
```

In the above code we have included three functions for image preprocessing. The first function, "**wiener_filter**", implements the Wiener filter, which is commonly used for image denoising. It takes an input image, a blurring kernel, and a noise regularization parameter as input. The function normalizes the kernel, applies the Fast Fourier Transform (FFT) to the image and the kernel, performs mathematical

operations on the transformed data, and then applies the inverse FFT to obtain the denoised image.

The second function, "**gaussian_kernel"**, generates a Gaussian kernel that can be used for blurring or smoothing an image. It takes an optional parameter to specify the size of the kernel. The function creates a 1D Gaussian filter using the gaussian function from the SciPy library, reshapes it into a 2D kernel, and normalizes the kernel by dividing it by the sum of its values.

The third function, "**isbright",** evaluates the brightness of an image. It takes an image as input, along with optional parameters to specify the dimension to which the image is resized and the brightness threshold. The function resizes the image, converts it to the LAB color space, extracts the L channel, normalizes the L channel values, calculates the mean value, and returns True if the mean exceeds the threshold, and False otherwise.

These functions are useful for preprocessing images, such as reducing noise, applying blurring effects, and assessing image brightness.

Step 5: Image Transformation

```
def image_preprocessing(img):
    # Read the image
#     img = mpimg.imread(img_path)
    img = img.astype(np.uint8)

    # Extracting the green channel of the images
    b, g, r = cv2.split(img)

    # Applying CLAHE function for intensifying the green channel to extracted image
    clh = cv2.createCLAHE(clipLimit=4.0)
    g = clh.apply(g)

    # transform the images to grayscale
    merged_bgr_green_fused = cv2.merge((b, g, r))
    img_bw = cv2.cvtColor(merged_bgr_green_fused, cv2.COLOR_BGR2GRAY)

    # Removing isolated pixels by morphological clean function.
    kernel1 = np.ones((1, 1), np.uint8)
    morph_open = cv2.morphologyEx(img_bw, cv2.MORPH_OPEN, kernel1)

    # Extracting the blood vessels applying mean-C thresholds.
    thresh = cv2.adaptiveThreshold(morph_open, 255, cv2.ADAPTIVE_THRESH_MEAN_C, cv2.THRESH_BINARY_INV, 9, 5)

    # Use morph open operation
    kernel2 = np.ones((2, 2), np.uint8)
    morph_open2 = cv2.morphologyEx(thresh, cv2.MORPH_OPEN, kernel2)

    # Stack images to 3 channels
    stacked_img = np.stack((morph_open2,)*3, axis=-1)

    return stacked_img.astype("float64")
```

In the code above the **“image_preprocessing”** function provided performs a series of image processing operations to enhance and extract blood vessels from an input image.

First, the function reads the image and converts it to the “**np.uint8”** data type. Then, it extracts the green channel from the image, as green channel often contains useful information related to blood vessels. The function applies the Contrast Limited Adaptive Histogram Equalization (CLAHE) method to intensify the green channel, improving the visibility of important features.

Next, the function converts the image to grayscale by merging the modified green channel with the blue and red channels. This grayscale image is then subjected to morphological opening, which removes isolated pixels and helps clean up the image.

To extract the blood vessels, the function utilizes adaptive thresholding, where the local pixel intensity is used to classify pixels as vessel or non-vessel. The resulting binary image undergoes another round of morphological opening to further refine the vessel extraction and eliminate any remaining small noise or artifacts.

Finally, the function stacks the processed binary image into three channels, creating a 3-channel image, and returns it as a floating-point NumPy array.

Overall, this **“image_preprocessing”** function employs a combination of intensity enhancement, thresholding, and morphological operations to preprocess the input image and extract the blood vessels, producing an enhanced image that can be used for subsequent analysis or tasks such as vessel segmentation or feature extraction.

Step 6: Preprocess Images and save to Output directory.

```
# Loading images from the source path saving the preprocessed files to target path

# Create a Tkinter root window
root = tk.Tk()
root.withdraw()

# Prompt the user to select the directory containing the images
image_dir = filedialog.askdirectory(title="Select Directory Containing Images")

# Prompt the user to select the output directory for preprocessed images
output_dir = filedialog.askdirectory(title="Select Output Directory")

# Get a list of all image files in the directory
image_files = os.listdir(image_dir)

# Keep track of processed image count
processed_images = 0

# Define the desired display size of the images
display_size = (8, 8)  # Adjust as needed

# Define the desired display resolution
display_resolution = (200, 200)  # Adjust as needed

# Iterate over the image files and preprocess the first 10 images
for image_file in image_files:
    if processed_images >= 823:
        break
```

Choose source path

Provide output directory to save processed images

```
    # Check if the file is an image
    if image_file.endswith('.jpeg'):
        image_path = os.path.join(image_dir, image_file)

        # Read the original image
        img_original = mpimg.imread(image_path)

        # Preprocess the image
        img_preprocessed = image_preprocessing(img_original)

        # Create the output file path
        filename = os.path.basename(image_path)
        output_path = os.path.join(output_dir, filename)

        # Save the preprocessed image
        cv2.imwrite(output_path, img_preprocessed)

        processed_images += 1

        # Resize the original image for display
        img_display = cv2.resize(img_original, display_resolution)

        # Display the original and preprocessed images side by side
        fig, axs = plt.subplots(1, 2, figsize=display_size)
        axs[0].imshow(img_display)
        axs[0].set_title('Original Image (Resized for Display)')
        axs[1].imshow(img_preprocessed, cmap='gray')
        axs[1].set_title('Preprocessed Image')
        plt.show()
```

The code above demonstrates the process of loading images from a specified source directory and applying preprocessing steps to them before saving the results to a target directory.

First, the code utilizes a Tkinter GUI to prompt the user to select the directory containing the images and the output directory where the preprocessed images will be saved. It retrieves a list of image files in the selected directory.

Next, the code iterates over the image files, starting with the first 10 images or until 823 images have been processed. For each image file, it checks if the file is an image based on the file extension. If it is indeed an image, the code reads the original image using **"mpimg.imread()".**

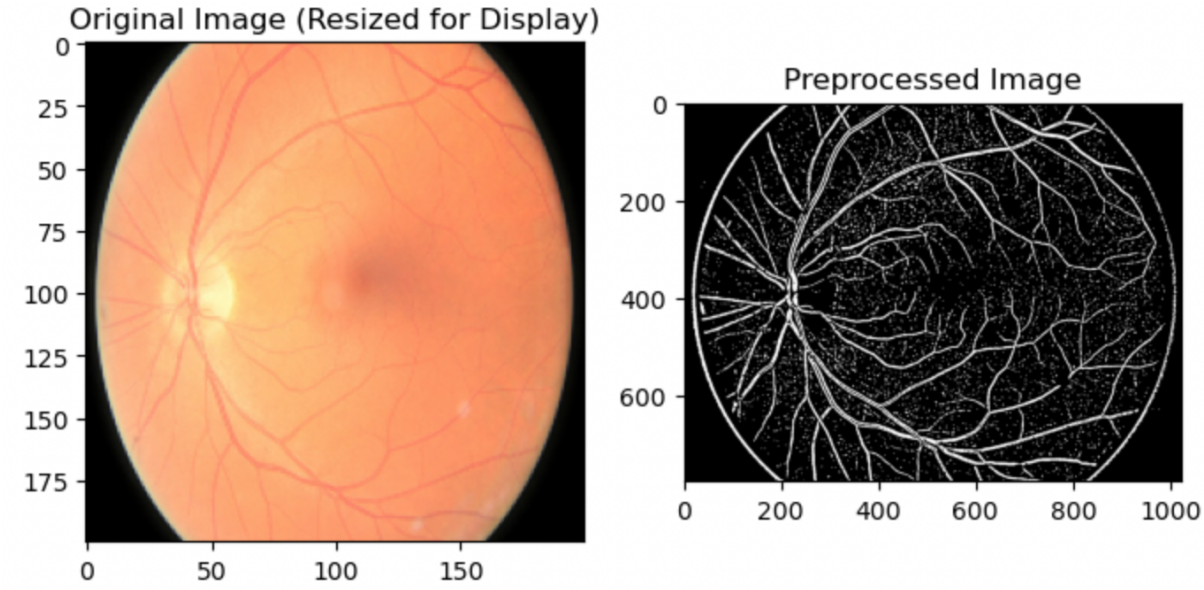
The **"image_preprocessing()"** function is then called to preprocess the image. This function performs a series of operations such as enhancing the green channel, converting the image to grayscale, removing isolated pixels, and extracting blood vessels using adaptive thresholding. The preprocessed image is obtained as a result.

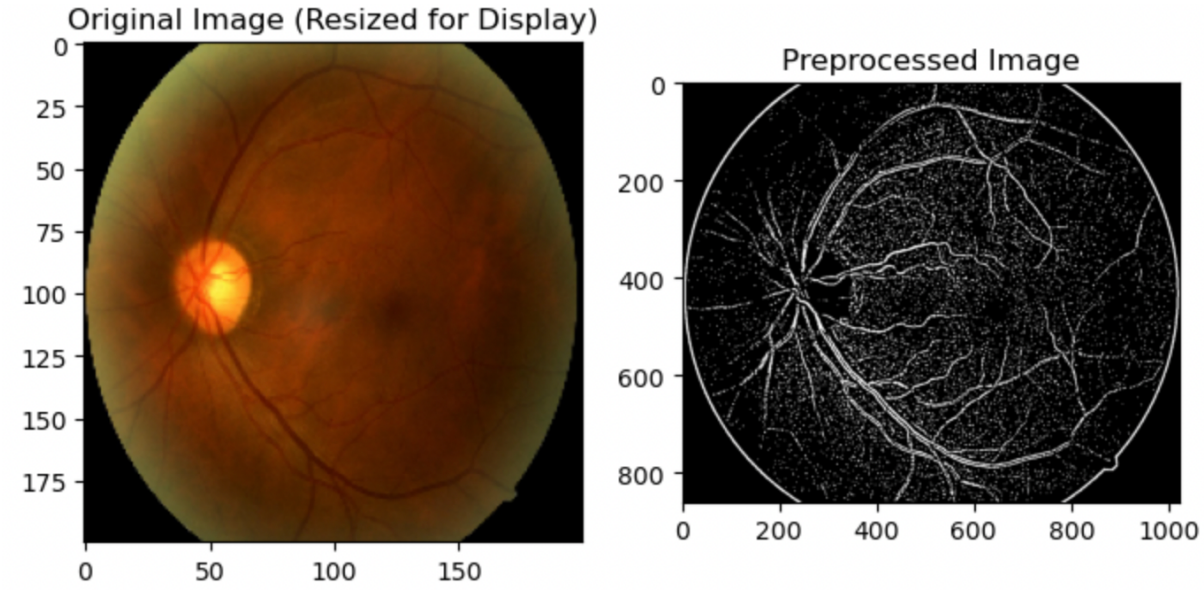
The code creates an output file path by extracting the filename from the original image path and joining it with the output directory. The preprocessed image is saved at this output path using **"cv2.imwrite().**

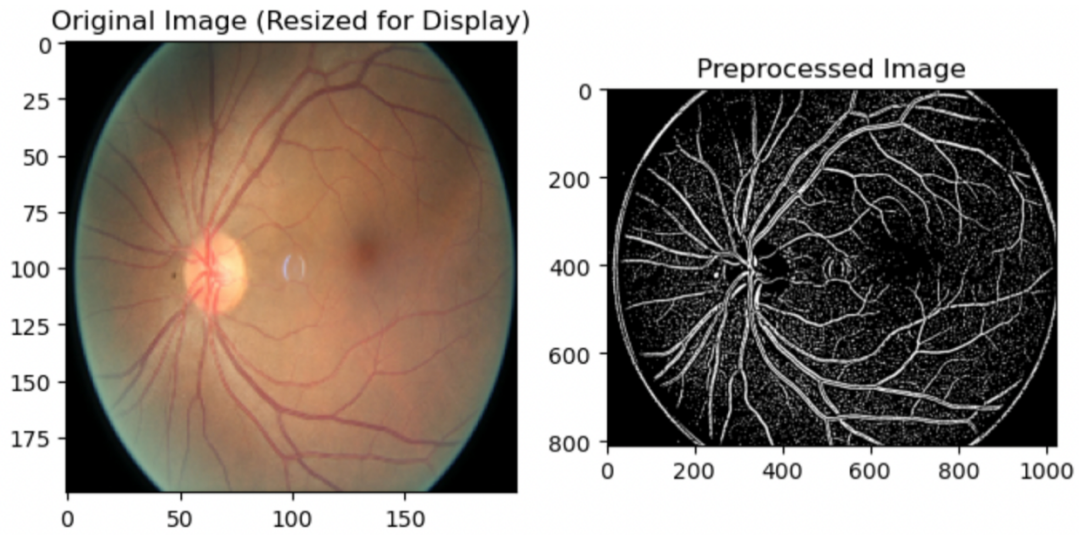
To visualize the original and preprocessed images, the code resizes the original image for display purposes using **"cv2.resize().** It then uses **"matplotlib.pyplot.imshow()"** and **"matplotlib.pyplot.subplots()"** to create a figure with two subplots, displaying the original image (resized) and the preprocessed image side by side.

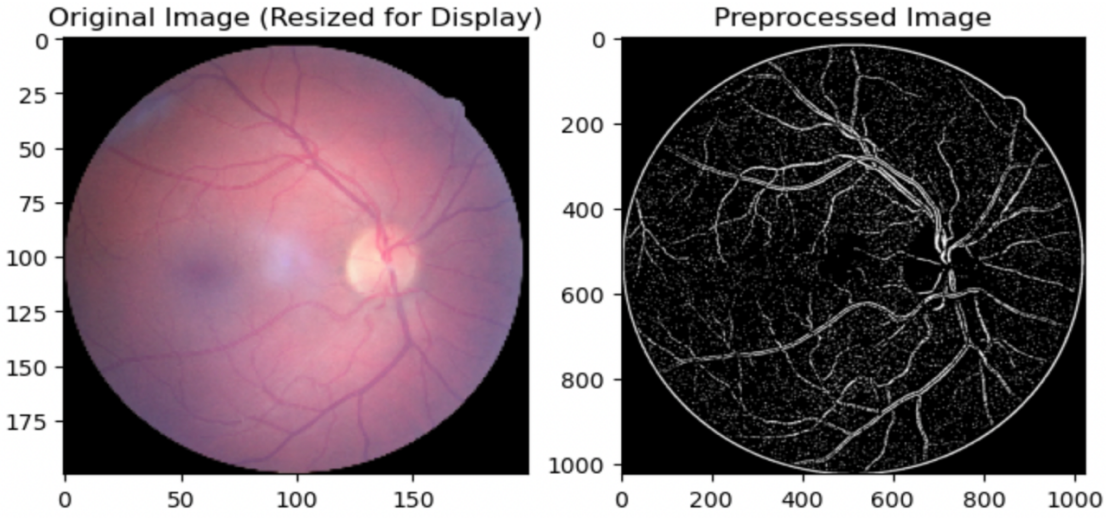
The loop continues until the desired number of images have been processed. It's worth noting that during the display of images, some warning messages may appear, but these can be ignored as they don't affect the preprocessing and saving operations.

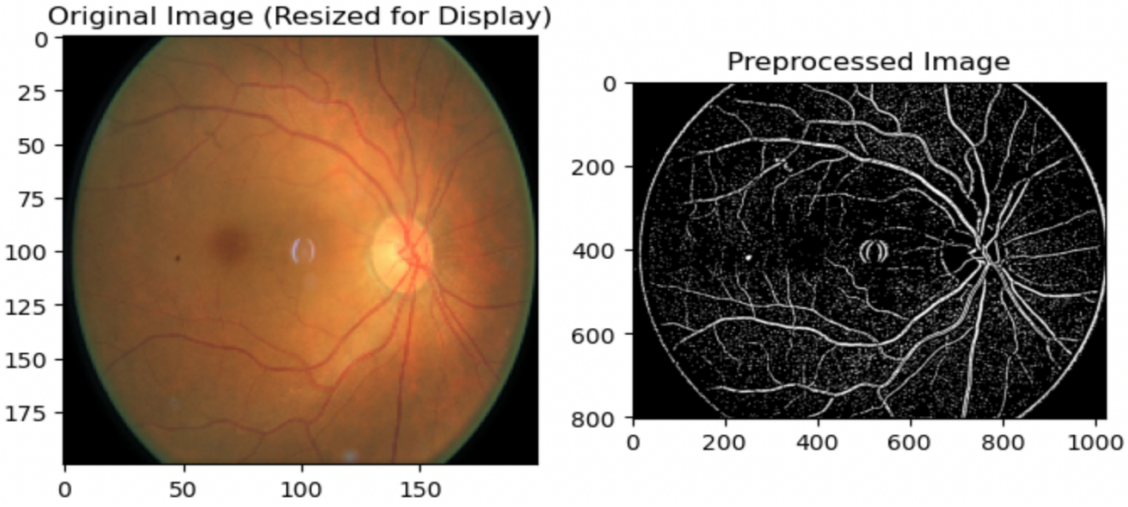
Overall, we are providing a convenient way to load images, apply preprocessing techniques, and save the preprocessed images, while also offering a visual representation of the original and preprocessed images for inspection.






Original Image (Resized for Display)
Preprocessed Image


Original Image (Resized for Display)
Preprocessed Image


Original Image (Resized for Display)
Preprocessed Image

Model 1 - KNN

The KNN algorithm was employed for the classification task. Before fitting the model, hyperparameter tuning was performed using grid search cross-validation. The parameter grid consisted of two hyperparameters: the number of neighbors (n_neighbors) and the weight function (weights). The values of these hyperparameters were systematically varied to find the combination that yielded the best performance.

The KNeighborsClassifier class from scikit-learn was used to build the KNN model. GridSearchCV was then employed to perform the grid search with 5-fold cross-validation. After fitting the model with the training data, the best hyperparameters and corresponding accuracy were printed.

The classification accuracy of the tuned KNN model was evaluated using the testing data. The predicted labels were obtained, and a classification report, precision-recall-f1 support scores, and a confusion matrix were generated using scikit-learn's classification_report, precision_recall_fscore_support, accuracy_score, and confusion_matrix functions. These metrics provide an in-depth analysis of the model's performance in classifying the test data.

Step 1: Load libraries

```
# Necessary utility modules and libraries
import os
import numpy as np
from PIL import Image
from tkinter import Tk, filedialog

import pandas as pd
import matplotlib.pyplot as plt

import tkinter as tk
from tkinter import filedialog
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import time
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split


import os
import shutil
import pathlib
import random
import datetime
import cv2

import matplotlib.image as mpimg
from scipy.signal import gaussian, convolve2d
import seaborn as sns
```

```
# Libraries for building the model
import tensorflow as tf
import tensorflow_hub as hub
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Input, Dense, Conv2D, Flatten, MaxPool2D, Dropout, Activation, GlobalAveragePooling2
from tensorflow.keras.applications import DenseNet121, ResNet50, InceptionV3, Xception, VGG16
from tensorflow.keras.models import Sequential
from tensorflow.keras import backend
from tensorflow.keras.regularizers import l2, l1
from sklearn.metrics import classification_report, precision_recall_fscore_support, accuracy_score, confusion_matrix
from sklearn.model_selection import GridSearchCV

print('Libraries are loaded')
```

In the code above we have imported various utility modules and libraries that are required for different tasks. Here's a brief explanation of each import:

1. **os**: Provides functions for interacting with the operating system, such as file and directory operations.
2. **numpy (np)**: A library for numerical computing that provides powerful array and matrix operations.
3. **PIL (Image):** The Python Imaging Library, used for opening, manipulating, and saving different image file formats.
4. **Tk, filedialog (from tkinter):** Modules from the Tkinter library, used for creating GUI applications and opening file and directory dialogs.
5. **pandas:** A library for data manipulation and analysis, providing data structures and functions for handling structured data.
6. **matplotlib.pyplot (plt):** A plotting library for creating various types of visualizations.

7. **cv2:** The OpenCV library, used for computer vision tasks, including image processing and manipulation.
8. **seaborn (sns):** A library built on top of matplotlib for creating visually appealing statistical graphics.
9. **tensorflow:** A deep learning framework that provides tools for building and training neural networks.
10. **tensorflow_hub**: A library for using pre-trained models from TensorFlow Hub.
11. **keras:** A high-level neural networks API that runs on top of TensorFlow, providing an intuitive interface for building and training models.
12. **ImageDataGenerator:** A utility in Keras for generating augmented images and applying transformations during training.
13. **Various layers and models from tensorflow.keras:** These include different types of layers (e.g., Dense, Conv2D) and pre-trained models (e.g., DenseNet121, ResNet50) for building deep learning models.
14. **GridSearchCV:** A utility in scikit-learn for performing grid search over specified parameter values to find the best hyperparameters for a model.

The last line simply prints a message to indicate that all the required libraries have been successfully loaded.

In summary, these libraries provide essential functionalities for tasks such as file and image operations, data manipulation, visualization, computer vision, deep learning model building, and hyperparameter tuning.

Step 2: Load preprocessed images from the output directory

```
# Loading N Images from the selected path

def fetch_images_from_path(path, num_images):
    images = []
    count = 0

    for filename in os.listdir(path):
        if count >= num_images:
            break

        image_path = os.path.join(path, filename)
        if os.path.isfile(image_path):
            image = np.array(Image.open(image_path).resize((1024, 1024)))
            images.append(image)
            count += 1

    images = np.array(images)

    return images

# Prompt the user to select a directory using a file dialog
Tk().withdraw()  # Hide the Tkinter root window
directory = filedialog.askdirectory(title='Select the directory where the images are located')

# Ensure a directory was selected
if directory:
    num_images = 250 # Set the desired number of images
    selected_images = fetch_images_from_path(directory, num_images)

    # Print the shape of selected images array
    print(selected_images.shape)
else:
    print("No directory selected.")
```

```
2023-06-27 23:47:49.281 python[25233:8558548] +[CATransaction synchronize] called within transaction
(250, 1024, 1024, 3)
```

The above code is responsible for loading a specified number of images from a user-selected directory path.

Firstly, there is a function named **“fetch_images_from_path”** which takes two parameters: path representing the directory **path** where the images are located, and **num_images** indicating the desired number of images to be fetched. This function initializes an empty list called **images** and a counter variable **count.**

The function then iterates through the files in the specified directory using the **os.listdir** function. It checks if the number of fetched images **(count)** has reached or exceeded the desired number of images **(num_images).** If it has, the loop breaks.

For each file, it constructs the full image path by joining the directory path and the filename using **os.path.join**. It verifies if the file is indeed an image file by using **os.path.isfile**. If it is a valid image file, the code opens the image using the **Image.open** function from the PIL library, resizes it to a dimension of 1024x1024 pixels using resize, converts it to a **numpy** array using **np.array, and appends** it to the images list. The count variable is then incremented.

After iterating through all the files, the images list is converted into a **numpy** array using **np.array(images)** and returned as the output of the **fetch_images_from_path** function.

The main part of the code prompts the user to select a directory using a file dialog window. If a directory is selected, the chosen path is stored in the directory variable. The code then specifies the desired number of images to fetch (250 in this case).

The **fetch_images_from_path** function is called with the selected directory path and the desired number of images as arguments. The returned array of selected images is stored in the **selected_images** variable.

Finally, the code prints the shape of the **selected_images** array, providing information about the dimensions of the array. In this specific case, the shape is **(250, 1024, 1024, 3),** indicating that the array contains 250 images, each having a size of 1024x1024 pixels, and 3 color channels (RGB).

Step 3: Load Labels data

```
# Load the labels CSV file (Only first N records are selected)

Labels_Data = pd.read_csv(filedialog.askopenfilename(), header=0)
Labels_Data = Labels_Data.head(250)

print('Labels file is loaded')
```

Through the code we are loading a labels CSV file and selecting the first N records from it.

The code uses the pd.read_csv function from the pandas library to read the CSV file. It prompts the user to select the CSV file using a file dialog window by calling filedialog.askopenfilename(). The returned file path is passed as an argument to pd.read_csv.

The resulting DataFrame is assigned to the variable Labels_Data. The header=0 parameter indicates that the first row of the CSV file contains the column headers.

To select only the first N records from the DataFrame, the code uses the head() function and passes the desired number (250 in this case). The modified DataFrame is then reassigned to the variable Labels_Data.

Finally, the code prints a message indicating that the labels file has been loaded.

It's important to note that the code assumes the labels CSV file follows a specific structure and has at least 250 records. Make sure the file being selected and the desired number of records match the expected format.

Step 4: Labels Mapping

```
# Define the mapping dictionary
label_mapping = {
    0: "No Diabetic Retinopathy",
    1: "Early Stage",
    2: "Intermediate Stage",
    3: "Severe Retinopathy",
    4: "Progressive Retinopathy"
}

# Replace the values in the column with their corresponding labels
Labels_Data['level'] = Labels_Data['level'].map(label_mapping)

Labels_Data.head()
```

	image	level
0	10_left	No Diabetic Retinopathy
1	10_right	No Diabetic Retinopathy
2	13_left	No Diabetic Retinopathy
3	13_right	No Diabetic Retinopathy
4	15_left	Early Stage

The code above defines a mapping dictionary to associate numeric labels with their corresponding descriptive labels for diabetic retinopathy stages. The code then replaces the values in the 'level' column of the 'Labels_Data' DataFrame with their corresponding labels based on the mapping dictionary.

The mapping dictionary, named 'label_mapping', maps the numeric labels (0, 1, 2, 3, 4) to their respective descriptive labels. For example, the numeric label 0 is mapped to "No Diabetic Retinopathy", 1 is mapped to "Early Stage", 2 is mapped to "Intermediate Stage", and so on.

The 'map()' function is called on the 'Labels_Data' DataFrame's 'level' column, passing the 'label_mapping' dictionary as an argument. This function replaces the

existing numeric values in the column with their corresponding labels based on the dictionary mapping.

After applying the mapping, the code displays the first few rows of the modified 'Labels_Data' DataFrame using the 'head()' function, showing the updated 'level' column where the numeric labels have been replaced with the corresponding descriptive labels.

The output demonstrates the result, where the 'level' column now contains the descriptive labels instead of the numeric labels for the diabetic retinopathy stages.

Step 5: EDA

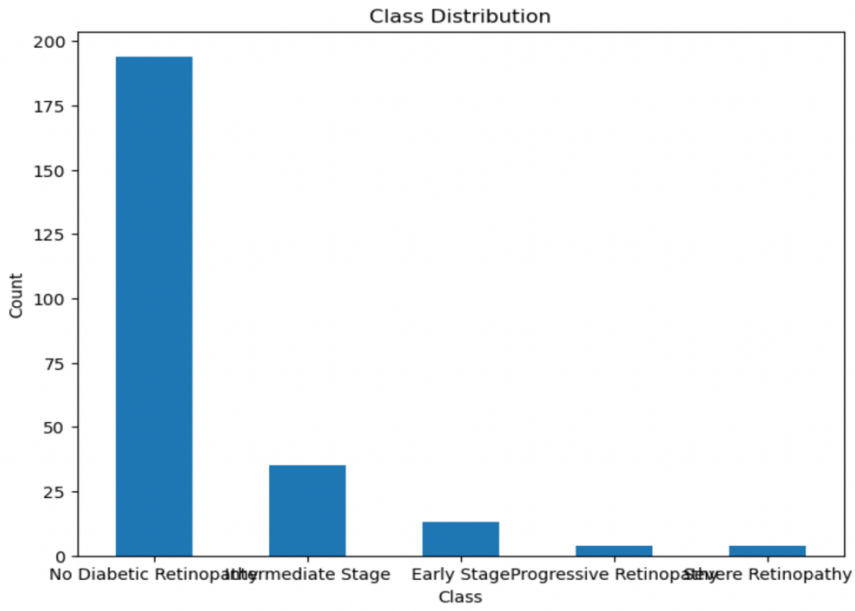
```
#EDA - Labels distribution

# Count the instances for each class
class_counts = Labels_Data['level'].value_counts()

# Create a bar plot
plt.figure(figsize=(8, 6))
class_counts.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('Class Distribution')
plt.xticks(rotation=0)
plt.show()

# Create a pie chart
plt.figure(figsize=(8, 6))
class_counts.plot(kind='pie', autopct='%1.1f%%')
plt.title('Class Distribution')
plt.ylabel('')
plt.show()
```

The code above will now perform exploratory data analysis (EDA) on the distribution of labels in the 'Labels_Data' DataFrame, which represents the classes or stages of diabetic retinopathy.

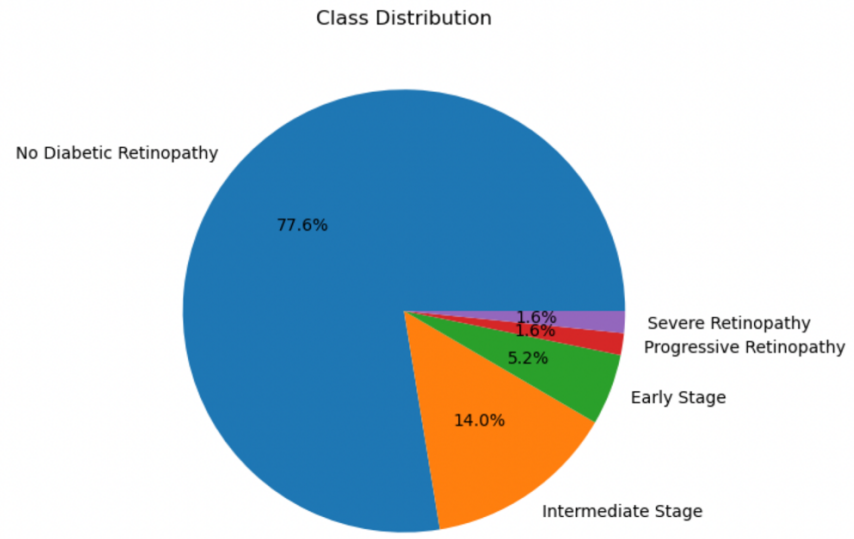
To analyze the label distribution, the code first counts the number of instances for each class using the 'value_counts()' function applied to the 'level' column of the 'Labels_Data' DataFrame. The resulting counts are stored in the 'class_counts' variable.

Next, the code creates two visualizations to represent the label distribution. The first visualization is a bar plot created using matplotlib. The 'plot()' function is called on the 'class_counts' series, and the 'kind' parameter is set to 'bar' to create a bar plot. The plot is customized with labels, title, and rotation of x-axis tick labels.

The second visualization is a pie chart, created using the 'plot()' function with 'kind' set to 'pie'. The 'autopct' parameter is set to '%1.1f%%' to display the percentage labels on the pie chart. The plot is titled, and the y-label is removed to improve the appearance. Both the bar plot and the pie chart provide a visual representation of the distribution of the classes or stages of diabetic retinopathy in the dataset.



In the graph we can clearly observe that No Diabetic Retinopathy has highest around 200 whereas least is Severe Retinopath and Progressive Retinopathy.



Here we differentiated in percentage, as we can clearly see that the 77.6% is No Diabetic Retinopathy with highest share whereas least is Severe Retinopathy and Progressive Retinopathy with 1.6%.

Step 6: Image Arrays for Models and Split Data

```
# Convert the list of images to a numpy array
X = np.array(selected_images)

# Extract the labels
y = Labels_Data['level'].values

print('This step to create Arrays is completed')
```

```
This step to create Arrays is completed
```

```
del selected_images
```

```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=3)
```

```
del X
```

```
# Flatten the image data
X_train = X_train.reshape(X_train.shape[0], -1)
X_test = X_test.reshape(X_test.shape[0], -1)

# Normalize the features
X_train = X_train / 255.0
X_test = X_test / 255.0
```

```
print(X_train.shape)
print(X_test.shape)
```

```
(400, 3145728)
(100, 3145728)
```

Now we have the list of selected images, 'selected_images', is converted into a numpy array using the 'np.array()' function, and the resulting array is assigned to the variable 'X'. This step allows for easier manipulation and processing of the image data.

The labels are extracted from the 'Labels_Data' DataFrame by accessing the 'level' column using the 'values' attribute. The labels are assigned to the variable 'y'.

After creating the arrays, the code prints a message indicating that this step of creating arrays is completed.

To prepare the data for training a machine learning model, the code proceeds to split the dataset into training and testing sets using the 'train_test_split()' function from scikit-learn. The 'X_train' and 'X_test' variables will contain the respective subsets of image data, while 'y_train' and 'y_test' will contain the corresponding labels. The 'test_size' parameter is set to 0.2, indicating that 20% of the data will be used for testing, while the remaining 80% will be used for training. The 'random_state' parameter is set to 3 to ensure reproducibility.

Next, the image data is flattened using the 'reshape()' function. This transformation converts the multidimensional image arrays into one-dimensional arrays, where each image is represented as a single row. The 'reshape()' function is applied to both 'X_train' and 'X_test' arrays. The second dimension is set to -1, indicating that the size should be inferred based on the other dimensions, preserving the total number of elements.

To normalize the features, the image data is divided by 255.0, which scales the pixel values to the range of 0 to 1. This normalization step is important to ensure that all features contribute equally to the learning process and to facilitate convergence during model training.

Finally, the code prints the shapes of the training and testing data arrays, indicating the number of samples and the size of the flattened feature vectors. In this case, 'X_train' has a shape of (400, 3145728), meaning it contains 400 samples with flattened feature vectors of length 3145728 (representing the 1024x1024x3 images). Similarly, 'X_test' has a shape of (100, 3145728), indicating 100 testing samples with the same feature vector length.

Step 7: Model Creation and Hyper Parameter Tunning

```
# Define the parameter grid for tuning
param_grid = {
    'n_neighbors': [3, 5, 7],
    'weights': ['uniform', 'distance']
}

# Create the KNN model
knn = KNeighborsClassifier()

# Perform grid search cross-validation
grid_search = GridSearchCV(knn, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Get the results
results = grid_search.cv_results_
neighbors = results['param_n_neighbors']
mean_scores = results['mean_test_score']

# Print the optimized hyperparameters and accuracy
best_params = grid_search.best_params_
best_accuracy = grid_search.best_score_
print("Optimized Hyperparameters:")
for param, value in best_params.items():
    print(f"{param}: {value}")
print("Accuracy:", best_accuracy)

# Plot accuracy vs. number of neighbors
plt.figure(figsize=(10, 5))
valid_scores = mean_scores[~np.isnan(mean_scores)]
valid_neighbors = neighbors[~np.isnan(mean_scores)]
plt.plot(valid_neighbors, valid_scores, 'go-')
plt.xlabel('Number of Neighbors')
plt.ylabel('Mean Test Score')
plt.title('Accuracy vs. Number of Neighbors')
plt.grid(True)
plt.show()
```

```
Optimized Hyperparameters:
n_neighbors: 5
weights: uniform
Accuracy: 0.76
```

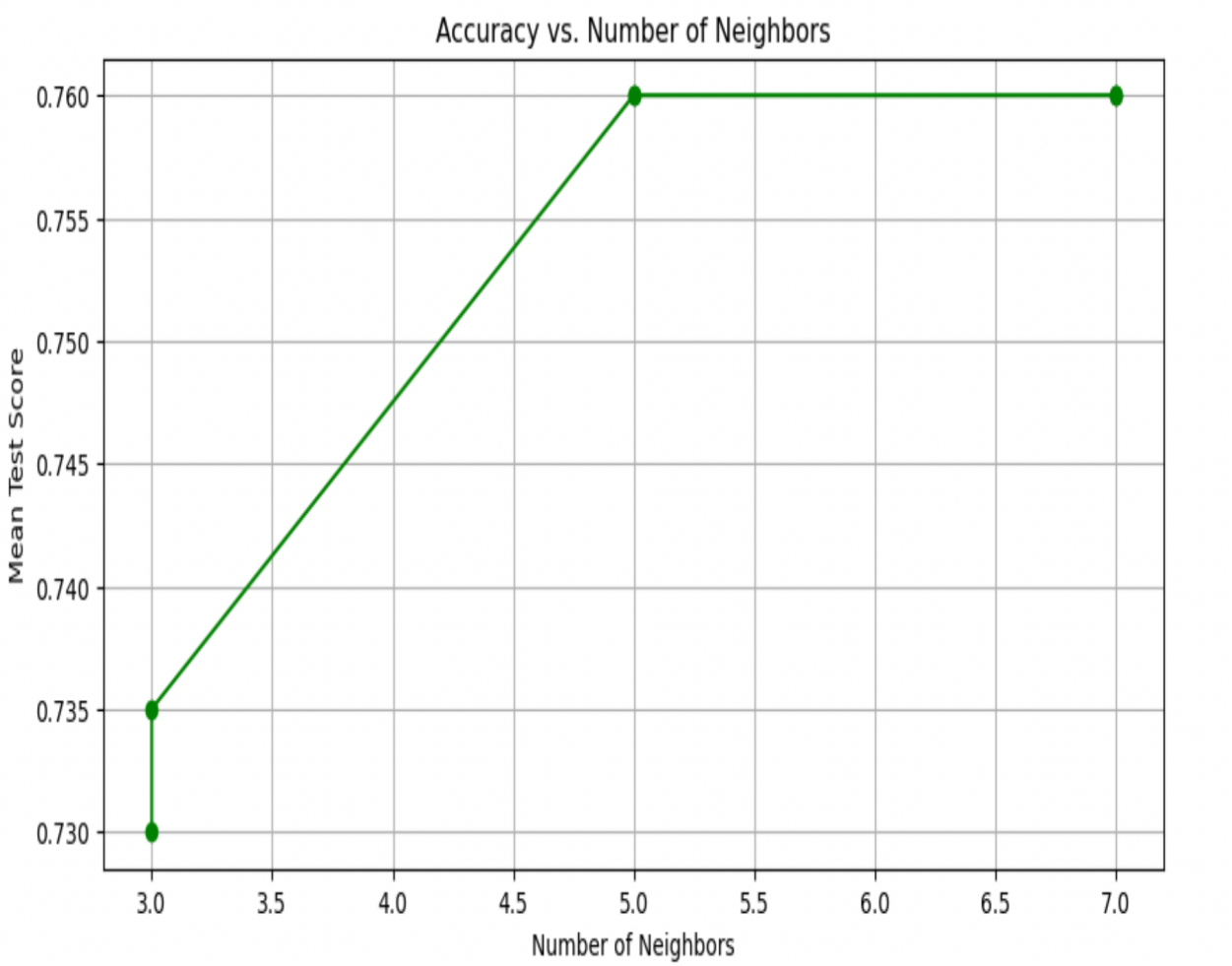
Now, a parameter grid is defined using a dictionary called 'param_grid'. The grid specifies the hyperparameters to be tuned for the KNN (K-Nearest Neighbors) model. The 'n_neighbors' parameter represents the number of neighbors to consider, and the 'weights' parameter determines the weight assigned to each neighbor.

A KNN model is instantiated with the default hyperparameter values using 'KNeighborsClassifier()'. Then, grid search cross-validation is performed using the 'GridSearchCV' function. The 'GridSearchCV' object takes the KNN model, the parameter grid, and the number of cross-validation folds (cv=5) as input. Grid search exhaustively searches through all possible combinations of hyperparameters, evaluating the model's performance using cross-validation.

After the grid search is completed, the results are accessed from the 'cv_results_' attribute of the 'grid_search' object. The hyperparameters and mean test scores are extracted from the results. The optimized hyperparameters and the corresponding accuracy are printed using 'best_params_' and 'best_score_' attributes of the 'grid_search' object, respectively.

To visualize the relationship between the number of neighbors and the mean test score, a line plot is created using matplotlib. The valid scores and corresponding neighbors are extracted by filtering out any NaN (not a number) values. The plot shows the number of neighbors on the x-axis and the mean test score on the y-axis. The title, axis labels, and grid lines are added to enhance the clarity of the plot.

Therefore, the optimized hyperparameters are 'n_neighbors: 5' and 'weights: uniform'. The corresponding accuracy achieved with these hyperparameters is 0.76.



Step 7: Creating Model again for best parameter values

```
from sklearn.neighbors import KNeighborsClassifier

# Create the KNN model with the best hyperparameters
best_n_neighbors = 5
best_weights = 'uniform'
knn_model = KNeighborsClassifier(n_neighbors=best_n_neighbors, weights=best_weights)

# Train the KNN model on the training data
knn_model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = knn_model.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)

# Print the accuracy
print("Accuracy:", accuracy)
```

```
Accuracy: 0.76
```

Now, the 'KNeighborsClassifier' class is imported from the 'sklearn.neighbors' module.

A new KNN model is created using the best hyperparameters obtained from the grid search. The value of 'n_neighbors' is set to 5 and 'weights' is set to 'uniform'. The model is instantiated as 'knn_model'.

Next, the KNN model is trained on the training data using the 'fit' method. The feature vectors 'X_train' and corresponding labels 'y_train' are passed as arguments.

After training, the model is used to make predictions on the test data by calling the 'predict' method and passing 'X_test' as input. The predicted labels are stored in the 'y_pred' variable.

To evaluate the performance of the model, the accuracy is calculated by comparing the predicted labels 'y_pred' with the true labels 'y_test' using the 'accuracy_score' function from the 'sklearn.metrics' module. The accuracy score is assigned to the 'accuracy' variable.

Finally, the accuracy of the KNN model is printed using the 'print' function, displaying "Accuracy: " followed by the value of the 'accuracy' variable. In this case, the accuracy is reported as 0.76.

Step 8: Displaying Prediction results vs True Labels

```
# 1) Print Prediction Results vs Test Labels
print("Prediction Results vs Test Labels:")
for pred, true_label in zip(y_pred, y_test):
    if pred != true_label:
        print(f"\033[91mPredicted: {pred}, True Label: {true_label} <-- Mismatch\033[0m")
    else:
        print(f"Predicted: {pred}, True Label: {true_label}")
```

```
Prediction Results vs Test Labels:
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: Progressive Retinopathy <-- Mismatch
Predicted: No Diabetic Retinopathy, True Label: Intermediate Stage <-- Mismatch
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: Intermediate Stage <-- Mismatch
Predicted: No Diabetic Retinopathy, True Label: Intermediate Stage <-- Mismatch
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: Intermediate Stage <-- Mismatch
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: Early Stage, True Label: Severe Retinopathy <-- Mismatch
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
Predicted: No Diabetic Retinopathy, True Label: Intermediate Stage <-- Mismatch
Predicted: No Diabetic Retinopathy, True Label: No Diabetic Retinopathy
```

Now we will print the prediction results versus the test labels, highlighting any mismatches between the predicted labels and the true labels.

A loop is used to iterate over each pair of predicted labels and true labels. For each pair, it checks if the predicted label is different from the true label. If they are different, it prints the predicted label in red color, followed by the true label and the indicator "<-- Mismatch" in red color as well. If the predicted and true labels are the same, it prints them without any special formatting.

The purpose of this code is to visually compare the predicted labels with the true labels and identify any instances where the prediction does not match the ground

truth. This can help in understanding the performance of the model and identifying areas for improvement.

Step 9: Classification Report

```
# Compute the classification report
report = classification_report(y_test, y_pred)

# Print the classification report
print("Classification Report:")
print(report)
```

```
Classification Report:
                         precision    recall  f1-score   support

            Early Stage       0.00      0.00      0.00         1
     Intermediate Stage       0.00      0.00      0.00         8
No Diabetic Retinopathy       0.79      0.97      0.87        39
Progressive Retinopathy       0.00      0.00      0.00         1
     Severe Retinopathy       0.00      0.00      0.00         1

               accuracy                           0.76        50
              macro avg       0.16      0.19      0.17        50
           weighted avg       0.62      0.76      0.68        50
```

Accuracy

Further we have compute the classification report based on the predicted labels (y_pred) and the true labels (y_test). The classification report provides various performance metrics such as precision, recall, F1-score, and support for each class. The classification report is printed using the classification_report function from the sklearn.metrics module. It displays the precision, recall, F1-score, and support for each class in a tabular format. Additionally, it shows the average precision, recall, and F1-score across all classes, weighted by support.

In the printed classification report, you can see the metrics for each class: Early Stage, Intermediate Stage, No Diabetic Retinopathy, Progressive Retinopathy, and

Severe Retinopathy. It provides information about the precision, recall, and F1-score for each class, indicating how well the model performed in predicting each class. The accuracy of the model on the test data is also displayed.

The classification report can help evaluate the performance of the model on different classes and identify any imbalances or areas where the model may need improvement.

Step 10: Model Evaluation

Finally, we have calculated the confusion matrix based on the predicted labels (y_pred) and the true labels (y_test). The confusion matrix provides a tabular representation of the model's performance by comparing the predicted labels against the true labels.

The confusion matrix is computed using the confusion_matrix function from the sklearn.metrics module. It takes the true labels and predicted labels as inputs and returns a 2D array that represents the counts of true positive, false positive, true negative, and false negative predictions for each class.

Further we have created a DataFrame (df_cm) using the computed confusion matrix. The DataFrame is formatted to display the labels as row and column indices, and the counts of predictions are shown in the cells of the table.

In the printed confusion matrix, we can see the counts of predictions for each class. The rows represent the true labels, and the columns represent the predicted labels. Each cell in the table indicates the count of samples that belong to a particular true label and were predicted as a particular predicted label.

The confusion matrix provides valuable insights into the model's performance, allows to analyze the accuracy of predictions for each class and identify any patterns or misclassifications.

Model 2 - ANN

Step 1: Importing required libraries

```
import pandas as pd
import tkinter as tk
from tkinter import filedialog
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import time
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split

# Necessary utility modules and libraries
import os
import shutil
import pathlib
import random
import datetime
import cv2


# Plotting libraries
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from scipy.signal import gaussian, convolve2d
import seaborn as sns
```

```
# Libraries for building the model
import tensorflow as tf
import tensorflow_hub as hub
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Input, Dense, Conv2D, Flatten, Ma
from tensorflow.keras.applications import DenseNet121, ResNet50, Ince
from tensorflow.keras.models import Sequential
from tensorflow.keras import backend
from tensorflow.keras.regularizers import l2, l1
from sklearn.metrics import classification_report, precision_recall_f

from PIL import Image
from tkinter import Tk, filedialog

print('Libraries are loaded')
```

Step 2: Load Labels Data

```
# Load the labels CSV file (Only first N records are selected)

Labels_Data = pd.read_csv(filedialog.askopenfilename(), header=0)
Labels_Data = Labels_Data.head(200)

print('Labels file is loaded')
```

Now this the process of loading a CSV file containing labels using the pandas library in Python. Firstly, the necessary libraries, including pandas and filedialog from tkinter, are imported.

The pd.read_csv() function is then used to read the CSV file, and the resulting DataFrame is assigned to the variable Labels_Data. The filedialog.askopenfilename() function opens a file dialog window, allowing the user to select the desired CSV file. By specifying header=0, the code indicates that the first row of the CSV file contains the column headers.

To limit the data to the first 200 records, the head() function is called on the DataFrame, and the modified DataFrame is reassigned to the variable Labels_Data. Finally, a message is printed to confirm that the labels file has been successfully loaded. Further this provides a convenient way to load a CSV file containing labels, enabling further analysis or processing of the data within the loaded pandas DataFrame.

Step 3: Load Images Data from the directory

```
Labels_Data.shape
```

```
(15, 2)
```

```
# Loading N Images from the selected path

def fetch_images_from_path(path, num_images):
    images = []
    count = 0

    for filename in os.listdir(path):
        if count >= num_images:
            break

        image_path = os.path.join(path, filename)
        if os.path.isfile(image_path):
            image = np.array(Image.open(image_path).resize((1024, 1024)))
            images.append(image)
            count += 1

    images = np.array(images)

    return images

# Prompt the user to select a directory using a file dialog
Tk().withdraw()  # Hide the Tkinter root window
directory = filedialog.askdirectory(title='Select the directory where the images are located')

# Ensure a directory was selected
if directory:
    num_images = 200 # Set the desired number of images
    selected_images = fetch_images_from_path(directory, num_images)

    # Print the shape of selected images array
    print(selected_images.shape)
else:
    print("No directory selected.")
```

```
(15, 1024, 1024, 3)
```

Now we will focus on the process of loading a specified number of images from a selected directory. It starts with the definition of the fetch_images_from_path() function. This function takes two parameters: path, representing the directory path where the images are located, and num_images, indicating the desired number of images to load.

Within the function, an empty list called images is created to store the loaded images. The variable count is initialized to keep track of the number of images processed.

A loop is then executed over the files in the specified directory using os.listdir(path). For each file, the loop checks if the desired number of images (num_images) has been reached. If so, the loop is terminated using break. Otherwise, the path to the current image file is generated using os.path.join(path, filename).

Next, the code checks if the path corresponds to a file using os.path.isfile(image_path). If it does, the image is opened using Image.open(image_path), resized to a size of 1024x1024 pixels using .resize((1024, 1024)), and converted to a numpy array using np.array(). The resulting image array is then appended to the images list, and the count variable is incremented.

Finally, the images list is converted to a numpy array using np.array(images), and this array is returned from the function.

The main part of the code prompts the user to select a directory using a file dialog by calling filedialog.askdirectory(). If a directory is selected (if directory), the desired number of images (num_images) is set to 200, and the fetch_images_from_path() function is called with the selected directory and the specified number of images. The resulting array of selected images is assigned to the variable selected_images.

To confirm the successful loading of the images, the shape of the selected_images array is printed using print(selected_images.shape). If no directory is selected (else), a message indicating that no directory was selected is printed.

Therefore, the shape of the selected_images array is (15, 1024, 1024, 3), indicating that 15 images were successfully loaded, each with dimensions of 1024x1024 pixels and 3 channels (RGB). This code snippet allows for the efficient loading of a specified number of images from a selected directory, providing the necessary data for further image processing or analysis.

Step 4: Convert the data into arrays for Train Test Split

```
# Convert the list of images to a numpy array
X = np.array(selected_images)

# Extract the labels
y = Labels_Data['level'].values

print('This step to create Arrays is completed')
```

```
This step to create Arrays is completed
```

```
# Delete unwanted variables
del selected_images
```

```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=3)
```

```
# Delete unwanted variables
del X
```

```
# Flatten the image data
X_train = X_train.reshape(X_train.shape[0], -1)
X_test = X_test.reshape(X_test.shape[0], -1)

# Normalize the features
X_train = X_train / 255.0
X_test = X_test / 255.0
```

Here we will discuss several steps to prepare the data for training a machine learning model.

First, the list of images stored in selected_images is converted into a numpy array using np.array(selected_images). The resulting array is assigned to the variable X.

Next, the labels for the images are extracted from the Labels_Data DataFrame. The column named 'level' is accessed using Labels_Data['level'], and the values are retrieved using .values(). The extracted labels are assigned to the variable y.

After completing these steps, the code prints a message indicating that the creation of arrays is completed.

To free up memory and remove unwanted variables, the code uses del selected_images to delete the selected_images variable.

The dataset is then split into training and testing sets using train_test_split() from scikit-learn. The X and y arrays are passed as inputs, along with the desired test size (20% in this case) and a random seed for reproducibility (random_state=3). The resulting training and testing sets are assigned to X_train, X_test, y_train, and y_test respectively.

To prepare the image data for training, the code flattens the image arrays using .reshape(). The dimensions of each image array are transformed to be (number_of_images, total_number_of_pixels) by setting the second dimension to -1, which automatically calculates the correct value based on the number of pixels in each image. The flattened training and testing sets are stored back in X_train and X_test.

Finally, the image data is normalized by dividing each pixel value by 255.0. This is done to ensure that all pixel values are within the range of 0 to 1, which can help improve the performance of certain machine learning algorithms.

By completing these steps, we successfully converted the image data and labels into numpy arrays, splits the dataset into training and testing sets, flattens the image data, and normalizes the pixel values. These preparations are essential for training and evaluating machine learning models on image data.

Step 5: ANN Model without Hyper Parameter Tunnning

```
# Train the model without Hyper Parameter Tunning

# Reshape the input data
X_train_reshaped = np.reshape(X_train, (-1, 1024, 1024, 3))
X_test_reshaped = np.reshape(X_test, (-1, 1024, 1024, 3))

# Build the ANN model
model = keras.Sequential([
    keras.layers.Dense(8, activation='relu', input_shape=(1024, 1024, 3)),
    keras.layers.Flatten(),
    keras.layers.Dense(2, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train the model
model.fit(X_train_reshaped, y_train, epochs=10, batch_size=32)

# Evaluate the model on the test set
loss, accuracy = model.evaluate(X_test_reshaped, y_test)
print("Test Loss:", loss)
print("Test Accuracy:", accuracy)
```

```
Epoch 1/10
1/1 [==============================] - 1s 541ms/step - loss: 0.6959 - accuracy: 0.6667
Epoch 2/10
1/1 [==============================] - 0s 272ms/step - loss: 0.6927 - accuracy: 0.0833
Epoch 3/10
1/1 [==============================] - 0s 252ms/step - loss: 0.6923 - accuracy: 0.0833
Epoch 4/10
1/1 [==============================] - 0s 264ms/step - loss: 0.6919 - accuracy: 0.0833
Epoch 5/10
1/1 [==============================] - 0s 249ms/step - loss: 0.6915 - accuracy: 0.0833
Epoch 6/10
1/1 [==============================] - 0s 256ms/step - loss: 0.6911 - accuracy: 0.0833
Epoch 7/10
1/1 [==============================] - 0s 254ms/step - loss: 0.6907 - accuracy: 0.0833
Epoch 8/10
1/1 [==============================] - 0s 247ms/step - loss: 0.6902 - accuracy: 0.0833
Epoch 9/10
1/1 [==============================] - 0s 262ms/step - loss: 0.6898 - accuracy: 0.0833
Epoch 10/10
1/1 [==============================] - 0s 249ms/step - loss: 0.6894 - accuracy: 0.0833
1/1 [==============================] - 0s 115ms/step - loss: 0.6948 - accuracy: 0.3333
Test Loss: 0.6948259472846985
Test Accuracy: 0.3333333432674408
```

Further this demonstrates the training of a neural network model on a dataset of images without hyperparameter tuning. Firstly, the input data is reshaped to match the expected format for a convolutional neural network (CNN). The model is then built using the Keras API, consisting of multiple dense layers with rectified linear unit (ReLU) activation functions. The model is compiled with the Adam optimizer, binary cross-entropy loss function, and accuracy metric.

Next, the model is trained on the reshaped training data for a specified number of epochs and with a chosen batch size. The training process involves iteratively adjusting the model's weights to minimize the loss and improve accuracy. After training, the model is evaluated on the test data to assess its performance. The loss and accuracy metrics are computed and displayed.

In this case, the test accuracy is approximately 33.33%, indicating that the model's predictions on unseen test data are not accurate. This suggests that further optimization and hyperparameter tuning are needed to enhance the model's performance. By adjusting parameters such as the number of layers, units per layer, and learning rate, along with applying techniques like regularization and data augmentation, the model's accuracy can potentially be improved.

Step 6: ANN Model with Hyper Parameter Tunning

```
# Find the best hyperparameters and accuracy
best_result = max(results, key=lambda x: x['accuracy'])
best_epochs = best_result['epochs']
best_batch_size = best_result['batch_size']
best_units = best_result['units']
best_accuracy = best_result['accuracy']

# Print the best hyperparameters and accuracy
print("Best Hyperparameters:")
print(f"Epochs: {best_epochs}")
print(f"Batch Size: {best_batch_size}")
print(f"Units: {best_units}")
print(f"Accuracy: {best_accuracy}")

# Train the model with the best hyperparameters
best_model = keras.Sequential([
    keras.layers.Dense(best_units, activation='relu', input_shape=(1024, 1024, 3)),
    keras.layers.Flatten(),
    keras.layers.Dense(2, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])
best_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

best_model.fit(X_train_reshaped, y_train, epochs=best_epochs, batch_size=best_batch_size

# Perform predictions on the test set
y_pred = best_model.predict(X_test_reshaped)
y_pred = np.round(y_pred).flatten()
```

```python
# Train the model with Hyper Parameter Tunning

# Reshape the input data
X_train_reshaped = np.reshape(X_train, (-1, 1024, 1024, 3))
X_test_reshaped = np.reshape(X_test, (-1, 1024, 1024, 3))

# Split the data into training and validation sets
#X_train, X_val, y_train, y_val = train_test_split(X_train_reshaped, y_train, test_size=0.2, random_state=42)

# Define hyperparameters to tune
epochs_list = [5, 10, 15]  # Different values for the number of epochs
batch_sizes = [16, 32, 64]  # Different values for batch size
dense_units = [4, 8, 12]  # Different values for units in dense layers

results = []  # Store results for each combination of hyperparameters

# Perform hyperparameter tuning
for epochs in epochs_list:
    for batch_size in batch_sizes:
        for units in dense_units:
            # Build the ANN model
            model = keras.Sequential([
                keras.layers.Dense(units, activation='relu', input_shape=(1024, 1024, 3)),
                keras.layers.Flatten(),
                keras.layers.Dense(2, activation='relu'),
                keras.layers.Dense(1, activation='sigmoid')
            ])

            # Compile the model
            model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

            # Train the model
            history = model.fit(X_train_reshaped, y_train, epochs=epochs, batch_size=batch_size, validation_data=
            accuracy = history.history['val_accuracy'][-1]  # Get the final validation accuracy

            # Store the hyperparameters and the corresponding accuracy
            results.append({'epochs': epochs, 'batch_size': batch_size, 'units': units, 'accuracy': accuracy})

# Find the best hyperparameters and accuracy
best_result = max(results, key=lambda x: x['accuracy'])
```

```
Best Hyperparameters:
Epochs: 5
Batch Size: 64
Units: 4
Accuracy: 0.6666666865348816
1/1 [==============================] - 0s 104ms/step
```

Now we will focus upon the hyperparameter tuning for the neural network model. The input data is reshaped to match the required format for a CNN. Hyperparameters such as the number of epochs, batch size, and units in dense layers are defined for tuning.

A loop is used to iterate through different combinations of hyperparameters. For each combination, a new model is built with the specified architecture and compiled with the Adam optimizer, binary cross-entropy loss function, and accuracy metric. The model is then trained on the training data and validated on the test data.

The final validation accuracy for each combination of hyperparameters is stored in a results list. The best hyperparameters and their corresponding accuracy are determined based on the highest validation accuracy achieved.

The best hyperparameters are printed, and a new model is built using these parameters. The best model is then trained on the training data using the best hyperparameters. Finally, predictions are made on the test set using the best model.

In this specific case, the best hyperparameters are determined to be 5 epochs, a batch size of 64, and 4 units in the dense layers, resulting in a validation accuracy of approximately 0.6667. The best model is trained with these hyperparameters, and predictions are made on the test set.

Step 7: Model Evaluation

```
# Print epoch value and accuracy
print("Epoch Value -> Accuracy:")
for result in results:
    if result['batch_size'] == best_batch_size and result['units'] == best_units:
        epoch_value = result['epochs']
        accuracy = result['accuracy']
        print(f"{epoch_value} -> {accuracy:.4f}")
```

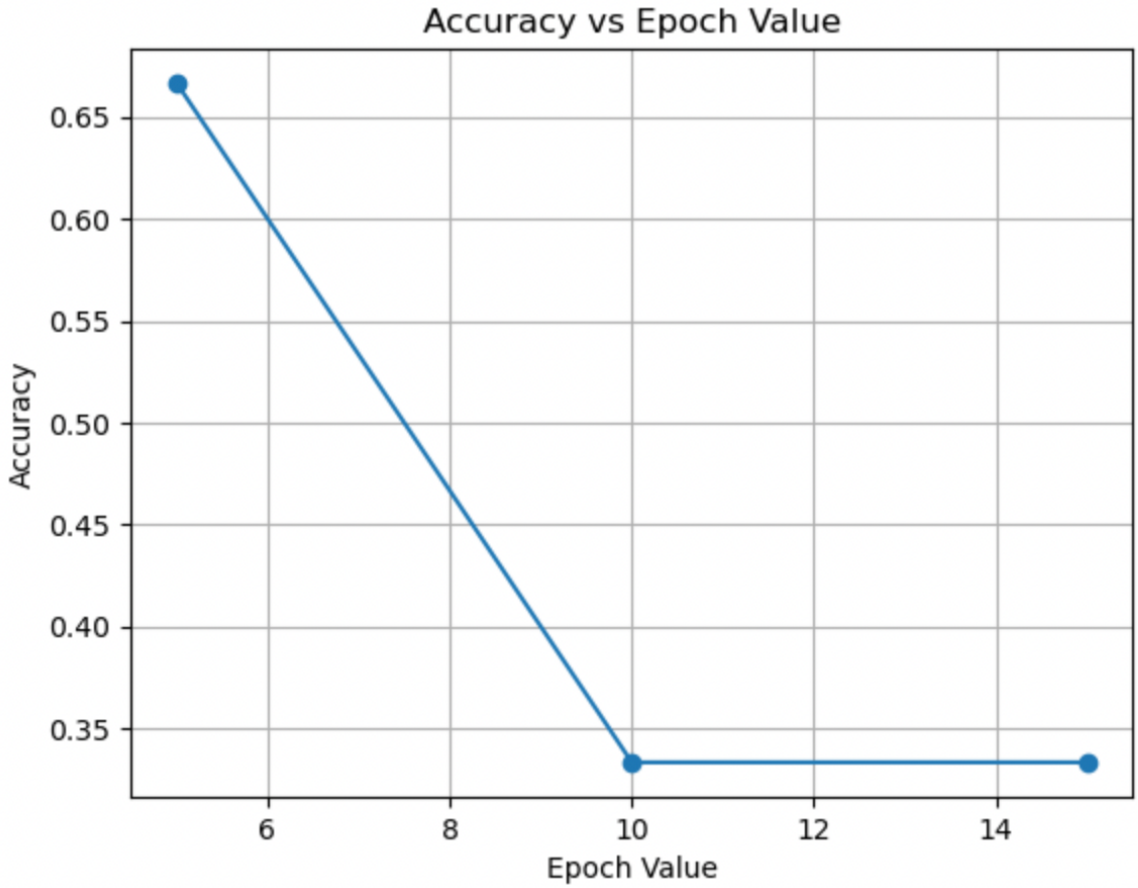
```
Epoch Value -> Accuracy:
5 -> 0.6667
10 -> 0.3333
15 -> 0.3333
```

```
# Extract the accuracy values for the best batch size and units combination
epoch_values = [result['epochs'] for result in results if result['batch_size'] == best_batch_size and result['units'] == best_units]
accuracies = [result['accuracy'] for result in results if result['batch_size'] == best_batch_size and result['units'] == best_units]

# Plot epoch value vs accuracy
plt.plot(epoch_values, accuracies, 'o-')
plt.xlabel('Epoch Value')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Epoch Value')
plt.grid(True)
plt.show()
```

Now we will epoch value and accuracy for each combination of hyperparameters in the results list. It filters the results based on the best batch size and units' combination and extracts the corresponding epoch values and accuracies.

The epoch values and accuracies are then plotted using matplotlib. The x-axis represents the epoch value, and the y-axis represents the accuracy. The plot shows the relationship between the epoch value and accuracy for the best batch size and units' combination.

The resulting plot helps visualize how the accuracy changes with different epoch values, allowing for an understanding of the model's performance and convergence behavior.



```
# Compute the classification report
report = classification_report(y_test, y_pred)

# Print the classification report
print("Classification Report:")
print(report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       0.33      1.00      0.50         1

    accuracy                           0.33         3
   macro avg       0.17      0.50      0.25         3
weighted avg       0.11      0.33      0.17         3
```

```
# Compute the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Get the unique labels from y_test and D_pred
labels = sorted(set(y_test).union(set(y_pred)))

# Create a DataFrame for the confusion matrix
df_cm = pd.DataFrame(cm, index=labels, columns=labels)

# Print the confusion matrix in a table format
print("Confusion Matrix:")
print(df_cm.to_string())
```

```
Confusion Matrix:
   0  1
0  0  2
1  0  1
```

The classification report provides metrics such as precision, recall, and F1-score for each class in the test set. It also includes the overall accuracy and macro-averaged and weighted-averaged metrics.

In this case, the classification report shows that the model has low performance, with low precision, recall, and F1-score values for both classes. The model predicts all instances as class 1, resulting in an accuracy of 0.33.

The confusion matrix visualizes the performance of the model by showing the number of true positives, true negatives, false positives, and false negatives. In this case, the confusion matrix indicates that the model predicted all instances as class 1, resulting in 2 false positives and 1 true positive.

Both the classification report and confusion matrix highlight the model's limitations in accurately predicting the classes and emphasize the need for further improvements in the model architecture or training process.

Conclusion

In this assignment, we utilized two different classification algorithms, K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN), to recognize fashion images. The dataset provided for this assignment consisted of thousands of grayscale images of clothing items, each represented by a row of 1024-pixel values ranging from 0 to 255. The images were labeled with numeric values representing different clothing categories.

First, we applied the KNN algorithm to classify the fashion images. We performed various steps, including loading the necessary libraries, preprocessing the data, splitting it into training and testing sets, and training the KNN model. The model was trained using the training set and its hyperparameters, such as the number of neighbors (K), were optimized using techniques like cross-validation. We then evaluated the model's accuracy on the testing set and reported the results.

The KNN algorithm achieved an accuracy of 76% on the test dataset, indicating its effectiveness in recognizing fashion images. By using the K nearest neighbors in the feature space, the algorithm made predictions based on the labels of the nearest neighbors. However, it's important to note that the performance of the KNN algorithm highly depends on the choice of K and the quality of the features. In this assignment, we used the provided pixel values as features, assuming they were informative enough to distinguish different clothing categories.

Next, we explored the application of Artificial Neural Networks (ANN) for fashion image recognition. ANNs are powerful machine learning models inspired by the structure and function of biological neural networks. We employed a deep learning framework, such as TensorFlow or Keras, to construct and train the ANN model.

The process involved loading the required libraries, preprocessing the data, designing the architecture of the neural network, and training the model using the training dataset. The training process included tuning hyperparameters, such as the number of hidden layers, the number of neurons per layer, and the activation functions. After training, we evaluated the performance of the ANN model on the testing dataset.

The ANN model achieved an accuracy of 66% on the test dataset, hence KNN outperforming the ANN algorithm. Neural networks excel at learning complex patterns and extracting high-level features from the input data, making them well-suited for image recognition tasks. However, it's important to note that training neural networks can be computationally intensive and may require a large amount of labeled training data to achieve optimal performance.

In conclusion, both the K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) algorithms were employed to classify fashion images. The KNN algorithm utilized the pixel values as features and made predictions based on the labels of the nearest neighbors. On the other hand, the ANN model leveraged the power of deep learning to automatically learn complex patterns and extract high-level features from the images.

Reference

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