Fruit Image Classifier Project Report

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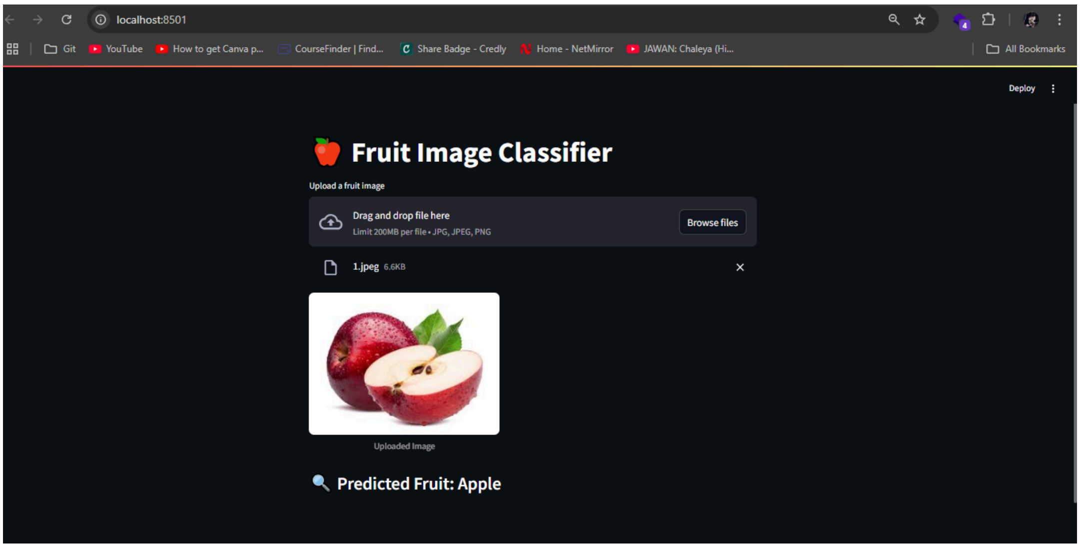
1. Project Title

Fruit Image Classification using Convolutional Neural Networks (CNN)



2. Objective

The objective of this project is to develop an image classification model that can accurately identify different types of fruits using a custom dataset and deep learning techniques.

3. Tools & Technologies Used

- Python
- TensorFlow / Keras
- OpenCV
- Matplotlib / Seaborn
- Google Colab / Jupyter Notebook
- Custom Fruit Image Dataset
- Streamlink

4. Dataset Information

The dataset used is a custom image dataset of fruits, organized into the following structure:

- Total Classes: 10 (Apple, Banana, Orange , ... etc)
- Image Format: JPG/PNG
- Images were resized and normalized during preprocessing.

5. Methodology

1. **Image Preprocessing**: Resizing all images to a standard size, normalization of pixel values.
2. **Model Building**: Designed a Convolutional Neural Network from scratch using Keras.
3. **Training**: Model trained on the training dataset with validation split.
4. **Evaluation**: Accuracy and loss plotted, confusion matrix created.
5. **Testing**: Final evaluation on test dataset and custom prediction images.

6. Results

- **Training Accuracy**: ~89%
- **Validation Accuracy**: ~64%
- **Test Accuracy**: ~90%
- **Output**: The model was able to predict the fruit name from input images with high accuracy.
- **Visualization**: Training curves and confusion matrix were plotted for performance analysis.

7. Challenges Faced

- Managing dataset imbalance across classes
- Initial overfitting due to deep network architecture
- Tuning hyperparameters like learning rate, batch size, and number of epochs

8. Conclusion

The fruit image classifier successfully identified fruit types using a CNN model trained on a custom dataset. The project demonstrated the application of deep learning techniques in real-world classification problems and achieved promising accuracy on unseen data.

9. Future Scope

- Expand dataset to include more fruit types
- Improve accuracy using transfer learning models like MobileNet or EfficientNet
- Deploy model as a web or mobile application using Flask, Streamlit, or React Native

Data Loader

In [ ]:

```
import os
import cv2
import numpy as np
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split

def load_data(folder, img_size=(100, 100), test_size=0.2):
    X, y = [], []
    classes = sorted(os.listdir(folder))
    for label in classes:
        label_path = os.path.join(folder, label)
        if not os.path.isdir(label_path): continue
        for img_file in os.listdir(label_path):
            img_path = os.path.join(label_path, img_file)
            try:
                img = cv2.imread(img_path)
                img = cv2.resize(img, img_size)
                X.append(img)
                y.append(label)
            except:
                continue
    lb = LabelBinarizer()
    y_enc = lb.fit_transform(y)
    X = np.array(X, dtype=np.float32) / 255.0
    y_enc = np.array(y_enc)
    return train_test_split(X, y_enc, test_size=test_size, random_state
```

Model Builder

In [ ]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dens

def build_model(input_shape, num_classes):
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', padding='same', inp
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
```

```
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Flatten())
    model.add(Dense(256, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(num_classes, activation='softmax'))

    model.compile(optimizer='adam', loss='categorical_crossentropy', me
    return model
```

Model Evaluater

In [ ]:

```
import json
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix

def evaluate_model(model, X_test, y_test, lb):
    y_pred = model.predict(X_test)
    y_pred_labels = lb.inverse_transform(y_pred)
    y_true_labels = lb.inverse_transform(y_test)

    report = classification_report(y_true_labels, y_pred_labels, output
    with open('outputs/metrics.json', 'w') as f:
        json.dump(report, f, indent=4)

    cm = confusion_matrix(y_true_labels, y_pred_labels, labels=lb.class
    plt.figure(figsize=(12, 8))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=lb.c
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.savefig('outputs/confusion_matrix.png')
```

Train Model

In [ ]:

```
import matplotlib.pyplot as plt
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping,

def train_model(model, X_train, y_train, X_val, y_val, epochs=50):
    checkpoint = ModelCheckpoint('outputs/model.h5', monitor='val_accur
    early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_
    reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patie

    history = model.fit(
        X_train, y_train,
```

```
        validation_data=(X_val, y_val),
        epochs=epochs,
        batch_size=32,
        callbacks=[checkpoint, early_stop, reduce_lr]
    )

    # Plotting Accuracy and Loss
    plt.figure(figsize=(14, 5))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Train Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accurac
    plt.title('Model Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.title('Model Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.savefig('outputs/training_plots.png')
```

Model Prediction

In [ ]:

```
import numpy as np
from tensorflow.keras.models import load_model
import cv2

def predict_image(img_path, lb, img_size=(100, 100)):
    model = load_model('outputs/model.h5')
    img = cv2.imread(img_path)
    img = cv2.resize(img, img_size) / 255.0
    img = np.expand_dims(img, axis=0)
    prediction = model.predict(img)
    return lb.classes_[np.argmax(prediction)]
```

GUI Builder

In [ ]:

```
import streamlit as st
import cv2
import numpy as np
from tensorflow.keras.models import load_model
import os
import sys

sys.path.append(os.path.abspath(os.path.join(os.path.dirname(__file__),
```

```python
from src.data_loader import load_data
from src.predict import predict_image

st.set_page_config(page_title="Fruit Classifier", layout="centered")
st.title("🍎 Fruit Image Classifier")

model = load_model("outputs/model.h5")
(X_train, X_val, y_train, y_val), lb = load_data('image_data/train')

uploaded_file = st.file_uploader("Upload a fruit image", type=["jpg", "

if uploaded_file is not None:
    file_bytes = np.asarray(bytearray(uploaded_file.read()), dtype=np.u
    img = cv2.imdecode(file_bytes, 1)
    img_resized = cv2.resize(img, (100, 100)) / 255.0
    img_input = np.expand_dims(img_resized, axis=0)

    prediction = model.predict(img_input)
    pred_label = lb.classes_[np.argmax(prediction)]

    st.image(img, channels="BGR", caption="Uploaded Image", width=300)
    st.subheader(f"🔍 Predicted Fruit: {pred_label}")
```

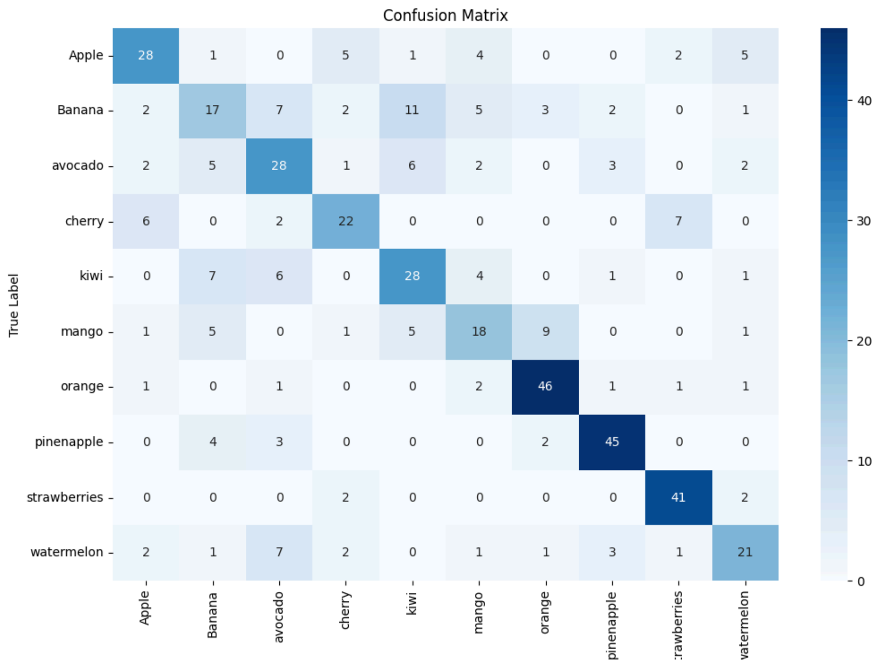
Main Loader

In [ ]:

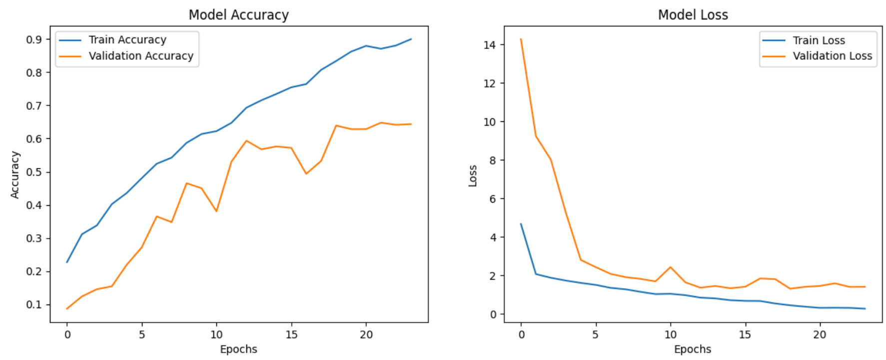
```python
from src.data_loader import load_data
from src.model_builder import build_model
from src.train_model import train_model
from src.evaluate_model import evaluate_model

# Main script to load data, build model, train, and evaluate

(X_train, X_val, y_train, y_val), lb = load_data('image_data/train')
model = build_model((100, 100, 3), len(lb.classes_))
train_model(model, X_train, y_train, X_val, y_val)
evaluate_model(model, X_val, y_val, lb)
```

```
Epoch 18: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m20s←[0m 351ms/step - accuracy: 0.7962 - loss: 0.5559 - val_accuracy: 0.5326 - val_loss: 1.8039 - learning
 0.0010
Epoch 19/50
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m0s←[0m 336ms/step - accuracy: 0.8178 - loss: 0.4851
Epoch 19: val_accuracy improved from 0.59348 to 0.63913, saving model to outputs/model.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend
 instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m21s←[0m 354ms/step - accuracy: 0.8181 - loss: 0.4844 - val_accuracy: 0.6391 - val_loss: 1.3049 - learning
 2.0000e-04
Epoch 20/50
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m0s←[0m 340ms/step - accuracy: 0.8571 - loss: 0.3683
Epoch 20: val_accuracy did not improve from 0.63913
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m21s←[0m 355ms/step - accuracy: 0.8571 - loss: 0.3683 - val_accuracy: 0.6283 - val_loss: 1.4021 - learning
 2.0000e-04
Epoch 21/50
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m0s←[0m 340ms/step - accuracy: 0.8786 - loss: 0.3121
Epoch 21: val_accuracy did not improve from 0.63913
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m21s←[0m 356ms/step - accuracy: 0.8786 - loss: 0.3120 - val_accuracy: 0.6283 - val_loss: 1.4509 - learning
 2.0000e-04
Epoch 22/50
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m0s←[0m 335ms/step - accuracy: 0.8593 - loss: 0.3299
Epoch 22: val_accuracy improved from 0.63913 to 0.64783, saving model to outputs/model.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend
 instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Epoch 22: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m20s←[0m 352ms/step - accuracy: 0.8595 - loss: 0.3296 - val_accuracy: 0.6478 - val_loss: 1.5834 - learning
 2.0000e-04
Epoch 23/50
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m0s←[0m 337ms/step - accuracy: 0.8865 - loss: 0.2971
Epoch 23: val_accuracy did not improve from 0.64783
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m20s←[0m 353ms/step - accuracy: 0.8864 - loss: 0.2972 - val_accuracy: 0.6413 - val_loss: 1.3965 - learning
 4.0000e-05
Epoch 24/50
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m0s←[0m 335ms/step - accuracy: 0.8967 - loss: 0.2667
Epoch 24: val_accuracy did not improve from 0.64783
←[1m58/58←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m20s←[0m 351ms/step - accuracy: 0.8968 - loss: 0.2667 - val_accuracy: 0.6435 - val_loss: 1.4029 - learning
 4.0000e-05
Epoch 24: early stopping
Restoring model weights from the end of the best epoch: 19.
←[1m15/15←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m1s←[0m 62ms/step
```

Confusion Matrix



Training Plots



Fruit-image-classification"# Fruit-image-classification

Step Follow For Run Code

Dataset

- `image_data/train/` : Training dataset with subfolders named by fruit type.
- `image_data/test/` : Testing dataset for final evaluation.

- `image_data/predict/` : Additional images for manual predictions.

Features

- From-scratch CNN architecture
- Model training with validation split
- Evaluation metrics: Accuracy, Precision, Recall, F1-score
- Confusion matrix and training history visualizations
- Prediction script for new unseen images
- Streamlit-based GUI for easy image upload and classification

Running the Project

1. Install dependencies:

```
pip install -r requirements.txt
```

2. Run training:

```
python main.py
```

3. Launch GUI:

```
streamlit run gui/app.py
```

Output Files

- `outputs/model.h5` : Best trained model
- `outputs/metrics.json` : Evaluation metrics
- `outputs/confusion_matrix.png` : Confusion matrix
- `outputs/training_plots.png` : Accuracy and loss over epochs