Configuration Manual

MSc Research Project
Programme Name

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MSc Project Submission Sheet

School of Computing

Student Name: Chinthulla Anish……………………………………..

Student ID: ………x23113081……………………………………………..……

Programme:……MSc in Data Analytics………………… **Year:** …2023……………..

Module: ……MSc in Research Project……………………………………………….………

Lecturer: …Prof. Hamilton Niculescu………………………………………………………….………

Submission Due Date: …24/04/2025…………………………………………………………………………..………

Project Title: …… Deep Learning-Based Detection of Shoplifting Stages: using 3DCNN and LRCN…………..………

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Configuration Manual

Deep Learning-Based Detection of Shoplifting Stages: using 3DCNN and LRCN

Anish Chinthulla
Student ID: x23113081

1 Project Overview

Deep Learning-Based Detection of Shoplifting Stages Using 3DCNN and LRCN".
The project investigates the effectiveness of two deep learning architectures—Long-Term Recurrent Convolutional Networks (LRCN) and Three-Dimensional Convolutional Neural Networks (3DCNN)—in detecting various stages of shoplifting behavior from surveillance footage. The models are trained and evaluated on real-world video data extracted from the UCF-Crime dataset to identify early indicators of suspicious activity.

2 Specification

2.1 Hardware Requirements

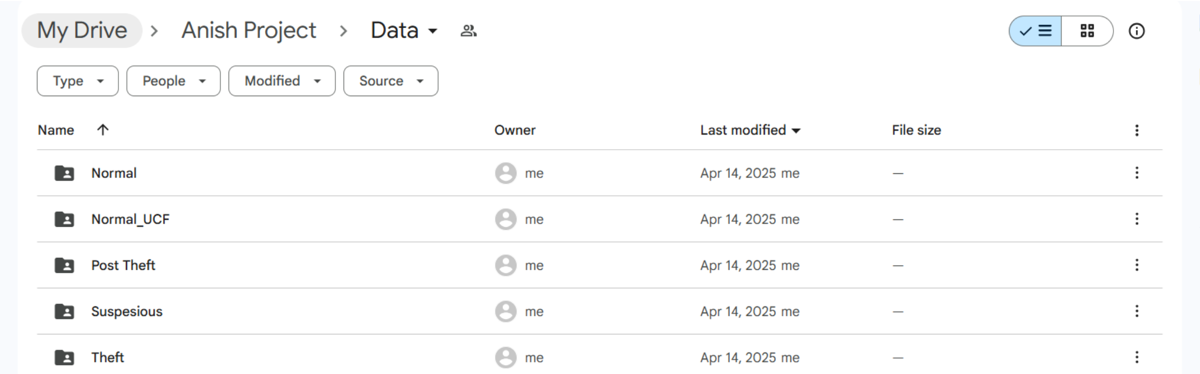
- **Processor:** Intel Core i7 or higher / AMD Ryzen equivalent
- **RAM:** Minimum 16GB
- **GPU:** NVIDIA CUDA-enabled GPU (RTX 2060 or better recommended)
- **Storage:** At least 50GB free disk space
- **Operating System:** Windows 10 / Ubuntu 20.04 LTS

2.2 Software Requirements

- **Programming Language:** Python (version 3.8+), selected for its extensive support in machine learning and computer vision tasks.
- **IDE:** Jupyter Notebook (via Anaconda distribution), widely used for interactive development and data analysis.
- **Cloud Platform:** Google Colab was utilized for training and testing deep learning models in a collaborative, cloud-based environment. It enabled GPU/TPU acceleration without the need for local computational resources, with Drive integration (drive.mount) for seamless data access and storage.
- **Libraries and Frameworks:**
    - **TensorFlow 2.x** and **Keras** for designing and training deep learning models.
    - **NumPy** and **OpenCV** for video processing and numerical computations.
    - **scikit-learn** for model evaluation and utility functions.
    - **Matplotlib** for visualizing performance metrics and training history.

3. Data Analysis and pre-processing

STEP 1-
The dataset was sourced from the UCF Crime Dataset. From this dataset, only the shoplifting-related data was extracted for further analysis. After segmenting the data into different categories — suspicious, theft, normal, and post-theft — the relevant segments were saved to Google Drive for storage and future use.



GOOGLE collab was used in the development of the code.

Mounting the drive into notebook

```
[ ]  from google.colab import drive
     drive.mount('/content/drive')
```

Imported libraries

1-importing-libraries

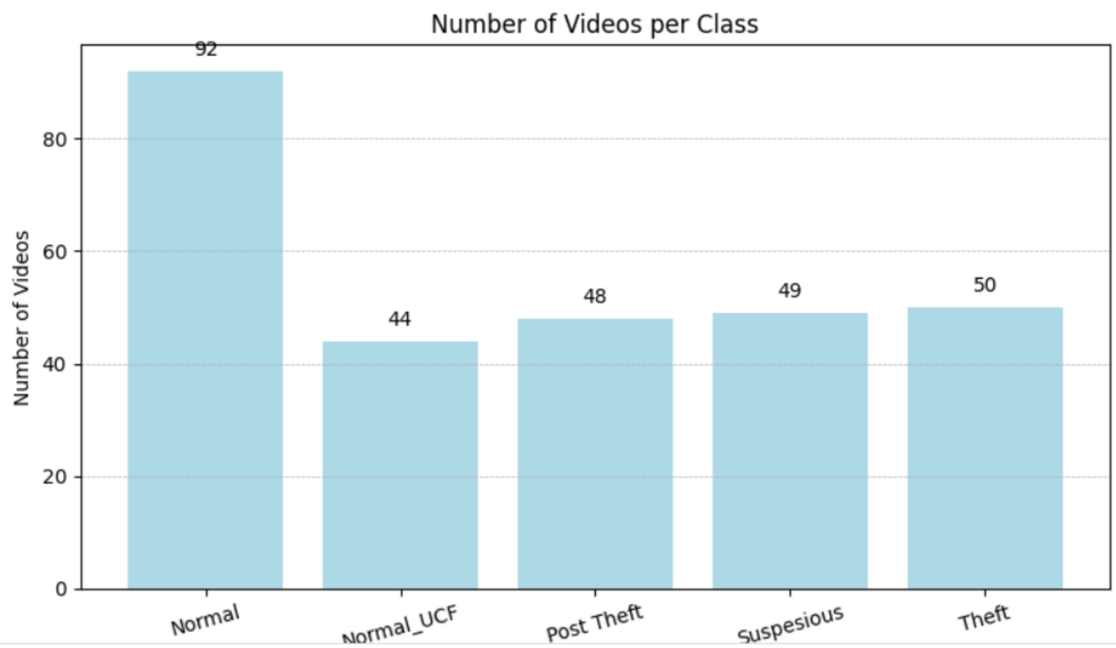
```
[ ]  import os
     import matplotlib.pyplot as plt
     import cv2
     import numpy as np
     import pandas as pd
```

Dataset path -

```
dataset_path = "/content/drive/MyDrive/Anish Project/Data"
dataset_path
```

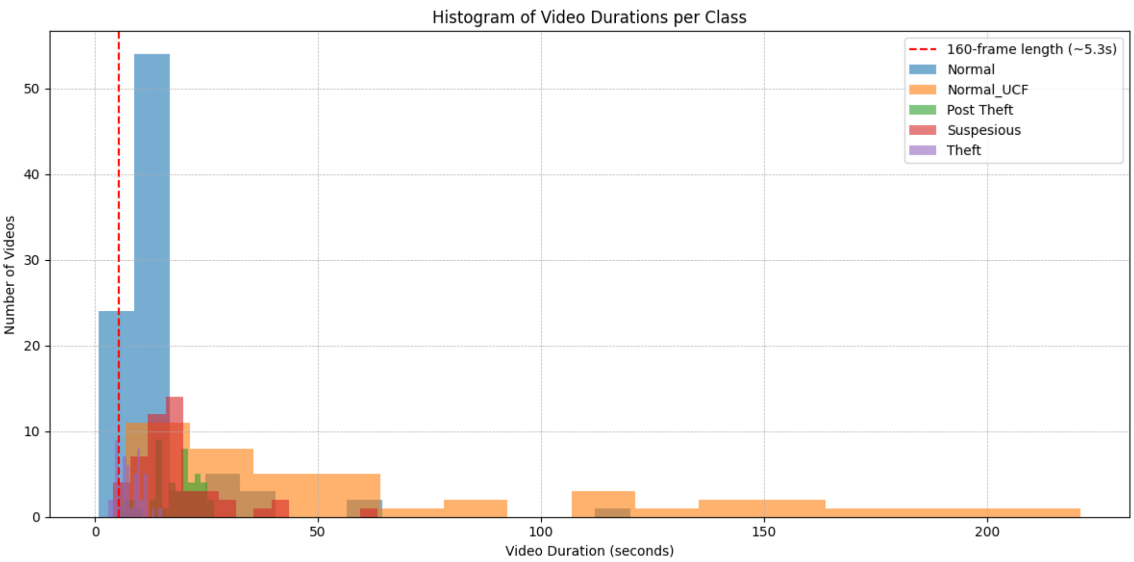
Step 2:- Number of Videos per Class

```
# Labels and values
labels = list(video_counts.keys())
counts = list(video_counts.values())

# Plot setup
plt.figure(figsize=(8, 5))
bars = plt.bar(labels, counts, color='lightblue')

# Add counts on top of each bar
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height + 2, str(int(height)),
             ha='center', va='bottom', fontsize=10)

# Final touches
plt.xlabel("Class")
plt.ylabel("Number of Videos")
plt.title("Number of Videos per Class")
plt.xticks(rotation=15)
plt.tight_layout()
plt.grid(axis='y', linestyle='--', linewidth=0.5)
plt.show()
```



Step 3.- Histogram for all the classes

```
[ ] durations_per_class = {}

    for class_name in sorted(os.listdir(dataset_path)):
        class_folder = os.path.join(dataset_path, class_name)
        if not os.path.isdir(class_folder):
            continue

        durations = []

        for video_file in os.listdir(class_folder):
            if not video_file.endswith(".mp4"):
                continue

            video_path = os.path.join(class_folder, video_file)
            cap = cv2.VideoCapture(video_path)

            fps = cap.get(cv2.CAP_PROP_FPS)
            frame_count = cap.get(cv2.CAP_PROP_FRAME_COUNT)

            if fps > 0:
                duration = frame_count / fps
                durations.append(duration)

            cap.release()

        durations_per_class[class_name] = durations

    # Plot histograms
    plt.figure(figsize=(12, 6))
    plt.axvline(x=5.3, color='red', linestyle='--', label='160-frame length (~5.3s)')

    for i, (class_name, durations) in enumerate(durations_per_class.items()):
        plt.hist(durations, bins=15, alpha=0.6, label=class_name)

    plt.xlabel("Video Duration (seconds)")
    plt.ylabel("Number of Videos")
    plt.title("Histogram of Video Durations per Class")
    plt.legend()
    plt.grid(True, linestyle='--', linewidth=0.5)
    plt.tight_layout()
    plt.show()
```

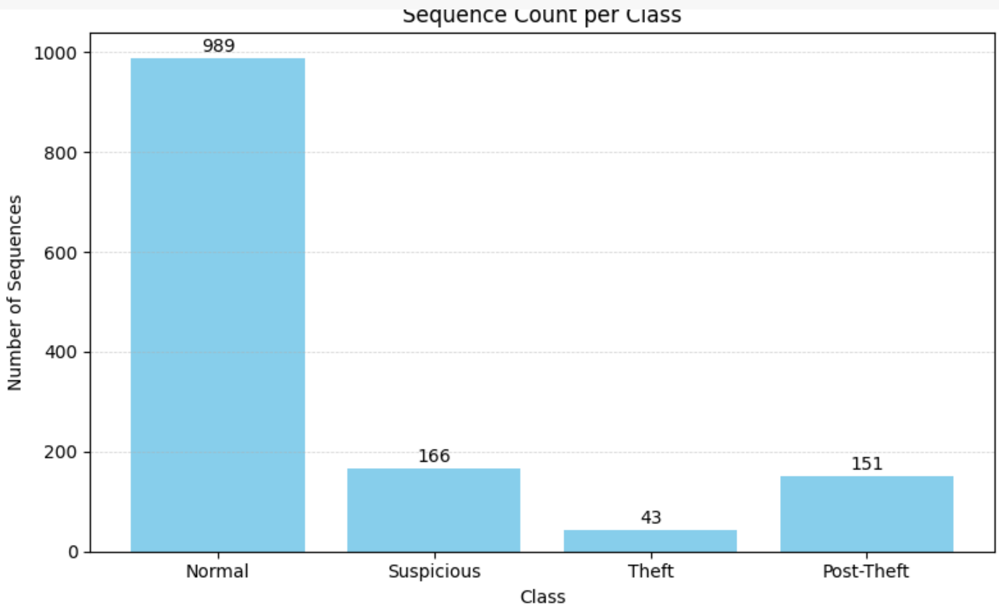


Step 5:- Reshaping the data into 120 frames and converting it into final shape of (120,64,64,1)

```
[ ] import os
    import cv2
    import numpy as np

    # Configuration
    VIDEO_ROOT = dataset_path
    SEQUENCE_LENGTH = 120
    FRAME_SIZE = (64, 64)  # Updated resolution

    # Label mapping: Normal_UCF + Normal = 0
    class_map = {
        "Normal": 0,
        "Normal_UCF": 0,
        "Suspesious": 1,
        "Theft": 2,
        "Post Theft": 3
    }

    X = []
    y = []

    # Process each class folder
    for class_name, label in class_map.items():
        folder_path = os.path.join(VIDEO_ROOT, class_name)
        if not os.path.isdir(folder_path):
            continue

        for video_file in os.listdir(folder_path):
            if not video_file.lower().endswith(".mp4"):
                continue

            video_path = os.path.join(folder_path, video_file)
            cap = cv2.VideoCapture(video_path)
            frames = []

            while True:
                ret, frame = cap.read()
                if not ret:
                    break

                gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
                resized = cv2.resize(gray, FRAME_SIZE)
                normalized = resized.astype("float32") / 255.0
                frames.append(normalized)

            cap.release()

            total = len(frames)
            if total < SEQUENCE_LENGTH:
                continue

            for i in range(0, total - SEQUENCE_LENGTH + 1, SEQUENCE_LENGTH):
                clip = frames[i:i + SEQUENCE_LENGTH]
                clip = np.array(clip).reshape(SEQUENCE_LENGTH, 64, 64, 1)
                X.append(clip)
                y.append(label)

            print(f"Processed {video_file} → {len(frames) // SEQUENCE_LENGTH} sequences")

    # Convert to NumPy arrays
    X = np.array(X)
    y = np.array(y)

    print("\nFinished sequence generation.")
    print(f"X shape: {X.shape}")
    print(f"y shape: {y.shape}")
```

Step 6 :- Number of frames per class after conversion.

```
[ ] import numpy as np
    import matplotlib.pyplot as plt

    # Class label mapping used earlier
    class_labels = {
        0: "Normal",
        1: "Suspicious",
        2: "Theft",
        3: "Post-Theft"
    }

    # Count each label in y
    unique, counts = np.unique(y, return_counts=True)

    # Prepare labels and values for plotting
    labels = [class_labels[i] for i in unique]
    values = counts

    # Print summary
    print("Number of sequences per class:")
    for label, count in zip(labels, values):
        print(f"{label}: {count}")

    # Plot
    plt.figure(figsize=(8, 5))
    bars = plt.bar(labels, values, color='skyblue')

    # Add labels on top of bars
    for bar, count in zip(bars, values):
        plt.text(bar.get_x() + bar.get_width() / 2, count + 5, str(count),
                 ha='center', va='bottom', fontsize=10)

    plt.title("Sequence Count per Class")
    plt.xlabel("Class")
    plt.ylabel("Number of Sequences")
    plt.grid(axis="y", linestyle="--", linewidth=0.5, alpha=0.6)
    plt.tight_layout()
    plt.show()
```



Step 7:- Test train split

Splitting Data for Training and Testing

```
[ ]  from sklearn.model_selection import train_test_split

     # Split the dataset with stratification
     X_train, X_test, y_train, y_test = train_test_split(
         X, y, test_size=0.2, random_state=42, stratify=y
     )

     # Display the shape of the new sets
     print("X_train:", X_train.shape)
     print("X_test: ", X_test.shape)
     print("y_train:", y_train.shape)
     print("y_test: ", y_test.shape)
```

```
X_train: (1079, 120, 64, 64, 1)
X_test:  (270, 120, 64, 64, 1)
y_train: (1079,)
y_test:  (270,)
```

4. Model

4.1 LRCN(Long-term Recurrent Convolutional Network)

Step 1. Model Architecture

```
[ ]  import os
     import tensorflow as tf
     from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import TimeDistributed, Conv2D, MaxPooling2D, BatchNormalization
     from tensorflow.keras.layers import Flatten, LSTM, Dense, Dropout
     from tensorflow.keras.optimizers import Adam

     # Input shape using 64x64 resized frames
     sequence_length = 120
     frame_height = 64
     frame_width = 64
     channels = 1
     input_shape = (sequence_length, frame_height, frame_width, channels)

     num_classes = 4  # Adjust to 3 if you merged theft + post-theft

     # Define the LRCN model
     model = Sequential()

     model.add(TimeDistributed(Conv2D(16, (3, 3), activation='relu'), input_shape=input_shape))
     model.add(TimeDistributed(MaxPooling2D(pool_size=(2, 2))))
     model.add(TimeDistributed(BatchNormalization()))

     model.add(TimeDistributed(Conv2D(32, (3, 3), activation='relu')))
     model.add(TimeDistributed(MaxPooling2D(pool_size=(2, 2))))
     model.add(TimeDistributed(BatchNormalization()))

     model.add(TimeDistributed(Flatten()))
     model.add(LSTM(128))  # LSTM kept as-is
     model.add(Dropout(0.5))
     model.add(Dense(num_classes, activation='softmax'))

     # Compile the model
     model.compile(
         loss='sparse_categorical_crossentropy',
         optimizer=Adam(learning_rate=0.0001),
         metrics=['accuracy']
     )

     model.summary()
```

Step 2 :- Model function and early stop and check point

```
[ ] from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

    # Path to save the best model weights
    checkpoint_path = os.path.join(os.getcwd(), 'checkpoint', 'LRCNClassification', 'checkpoint.weights.h5')
    os.makedirs(os.path.dirname(checkpoint_path), exist_ok=True)

    early_stopping = EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True,
        verbose=1
    )

    model_checkpoint = ModelCheckpoint(
        filepath=checkpoint_path,
        monitor='val_loss',
        save_best_only=True,
        save_weights_only=True,
        verbose=1
    )

    callbacks = [early_stopping, model_checkpoint]

    # Train the model
    history = model.fit(
        X_train, y_train,
        validation_data=(X_test, y_test),
        batch_size=4,
        epochs=50,
        callbacks=callbacks
    )
```

4.2 3D-CNN (Three-Dimensional Convolutional Neural Network)

Step 1:- Model Architecture

```
[ ] from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Conv3D, MaxPooling3D, BatchNormalization
    from tensorflow.keras.layers import Flatten, Dense, Dropout
    from tensorflow.keras.optimizers import Adam

    input_shape = (120, 64, 64, 1)
    num_classes = 4  # or 3 if you merged classes

    model = Sequential()

    model.add(Conv3D(32, kernel_size=(3, 3, 3), activation='relu', input_shape=input_shape))
    model.add(MaxPooling3D(pool_size=(1, 2, 2)))
    model.add(BatchNormalization())

    model.add(Conv3D(64, kernel_size=(3, 3, 3), activation='relu'))
    model.add(MaxPooling3D(pool_size=(2, 2, 2)))
    model.add(BatchNormalization())

    model.add(Conv3D(128, kernel_size=(3, 3, 3), activation='relu'))
    model.add(MaxPooling3D(pool_size=(2, 2, 2)))
    model.add(BatchNormalization())

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

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

    model.summary()
```

Step 2: Model function and early stop and check point

```
[ ] from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
    import os

    checkpoint_path = os.path.join(os.getcwd(), 'checkpoint', '3DCNN', 'checkpoint.weights.h5')
    os.makedirs(os.path.dirname(checkpoint_path), exist_ok=True)

    early_stopping = EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True,
        verbose=1
    )

    model_checkpoint = ModelCheckpoint(
        filepath=checkpoint_path,
        monitor='val_loss',
        save_best_only=True,
        save_weights_only=True,
        verbose=1
    )

    callbacks = [early_stopping, model_checkpoint]

    history = model.fit(
        X_train, y_train,
        validation_data=(X_test, y_test),
        batch_size=4,
        epochs=50,
        callbacks=callbacks
    )
```

5. Evaluation

In this research , parameter used for evaluvation both models are same

1.Classification report

```python
import numpy as np
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
import matplotlib.pyplot as plt

# Define class labels
class_labels = ['Normal', 'Suspicious', 'Theft', 'Post-Theft']

# Predict class probabilities
print('Finding predicted classes and probabilities to build confusion matrix')
predicted_probs = model.predict(X_test, verbose=1)

# Get predicted class indices
predicted_classes = np.argmax(predicted_probs, axis=-1)  # shape: (num_samples,)

# Ensure y_test is flattened
y_test_flat = y_test.flatten()

# Generate confusion matrix
cm = confusion_matrix(y_test_flat, predicted_classes)

# Plot confusion matrix with labels
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.tight_layout()
plt.show()

# Classification report
print("\nClassification Report:\n")
print(classification_report(y_test_flat, predicted_classes, target_names=class_labels))
```

2.Accuracy

```python
[ ]  from sklearn.metrics import accuracy_score

     # Get final training and validation accuracy from history
     final_train_accuracy = history.history['accuracy'][-1]
     final_val_accuracy = history.history['val_accuracy'][-1]

     # Predict on test set
     predictions = model.predict(X_test)
     predicted_classes = np.argmax(predictions, axis=1)
     true_classes = y_test

     # Compute test accuracy using sklearn
     final_test_accuracy = accuracy_score(true_classes, predicted_classes)

     # Print all three
     print("Final Training Accuracy:       ", round(final_train_accuracy * 100, 2), "%")
     print("Final Validation Accuracy:     ", round(final_val_accuracy * 100, 2), "%")
     print("Test Set Accuracy (Final Eval):", round(final_test_accuracy * 100, 2), "%")
```

3. Training accuracy vs testing accuracy & Losses plots

```
[ ]
    # Plot training history
    pd.DataFrame(history.history).plot()
    plt.title('Accuracy and Loss over Epochs')
    plt.xlabel('Epoch')
    plt.ylabel('Value')
    plt.grid(True)
    plt.show()

    # Plot training vs validation accuracy
    plt.figure(figsize=(8, 7))
    plt.plot(history.history['accuracy'], label='train', color='tomato')
    plt.plot(history.history['val_accuracy'], label='test', color='skyblue')
    plt.title('Model Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(loc='upper left')
    plt.grid(True)
    plt.show()

    plt.figure(figsize=(8, 7))
    plt.plot(history.history['loss'], label='train', color='tomato')
    plt.plot(history.history['val_loss'], label='test', color='skyblue')
    plt.title('Model Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(loc='upper right')
    plt.grid(True)
    plt.show()
```