CRIME-VISION - Advanced Crime Classification With Deep Learning

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1. INTRODUCTION

1.1. Overview and Purpose

Crime identification using deep learning is an innovative approach that utilizes advanced deep learning techniques to examine crime scenes and incidents by analyzing images and video footage. Its objective is to accurately identify and categorize various forms of criminal activities. Deep learning, a subset of machine learning, entails training neural networks with extensive data sets to discern patterns and make informed predictions or decisions. The integration of deep learning enables the examination of images and video recordings from crime scenes or incidents, facilitating the classification of distinct types of crimes based on the actions depicted within the visual content. The utilization of this methodology proves valuable across numerous domains within the criminal justice system and law enforcement, including crime scene investigation, forensic analysis, and surveillance.

Deep learning algorithms possess the capability to acquire knowledge of patterns and characteristics present in images and videos, which are pertinent to the identification of different criminal activities. Furthermore, these algorithms can evaluate substantial volumes of data, such as surveillance recordings, to detect prevailing trends and patterns within crime-related information. Consequently, this enables law enforcement agencies to develop strategic initiatives and interventions aimed at preventing criminal behavior.

By harnessing deep learning for crime identification, law enforcement agencies can benefit from enhanced capabilities in analyzing visual evidence. The automated classification of crimes based on image and video analysis streamlines the investigation process, providing valuable insights into criminal activities. This technology can assist forensic experts in their analysis of crime scenes, aiding in the identification of key evidence and facilitating the overall investigation. Additionally, deep learning algorithms can be utilized to conduct comprehensive evaluations of surveillance footage, identifying suspicious activities and generating alerts in real-time. Such proactive measures empower law enforcement to respond swiftly and effectively, preventing criminal acts and enhancing public safety.

2. Literature survey

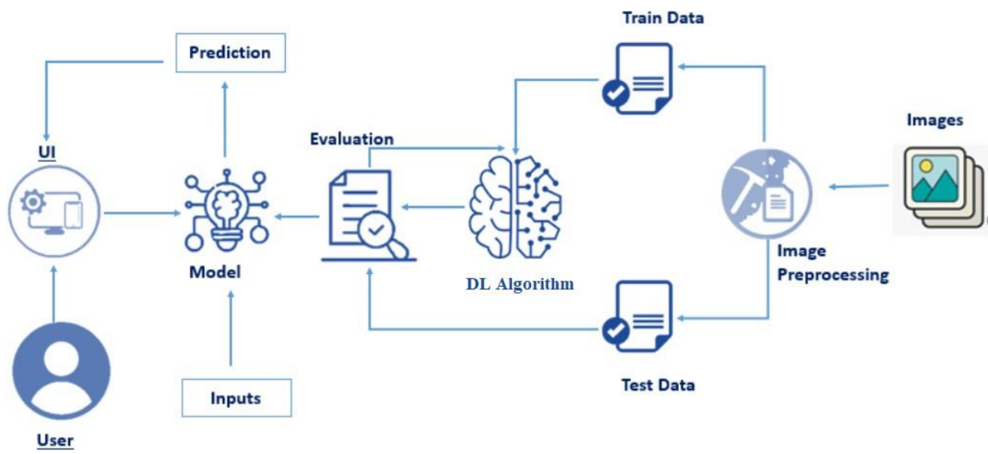
2.1. **Existing Problem:** The existing problem in the field of crime identification is the reliance on traditional methods for analyzing images and video footage of crime scenes. These methods often require manual intervention and lack the ability to effectively classify different types of crimes based on the activities depicted. Additionally, they may struggle to analyze large volumes of data and identify patterns or trends.

2.2. **Existing Approaches or Methods:** Current approaches to address this problem involve manual examination and interpretation of crime scene evidence, which can be time-consuming and subjective. Some existing methods also employ computer vision techniques to analyze images and videos, but they may not fully leverage the power of deep learning algorithms for accurate crime classification and pattern recognition.

2.3. **Proposed Solution:** Our proposed solution entails the use of deep learning techniques to enhance crime identification and classification. We have created a deep learning model using Densenet121 by using transfer learning . By training neural networks on large datasets of crime scene images and videos, we aim to enable automated analysis and classification of different types of crimes based on activity recognition. This approach allows for the extraction of relevant patterns and features from the visual data, leading to more accurate and efficient crime identification Furthermore, our proposed solution incorporates the analysis of vast amounts of surveillance footage to uncover trends and patterns in crime data. By leveraging deep learning algorithms for data analysis, law enforcement agencies can develop proactive strategies and interventions to prevent crime more effectively.

3. THEORETICAL ANALYSIS

3.1. Block diagram



3.2. Hardware/Software Designing:

3.2.1. Hardware:

3.2.1.1. A computer system with sufficient processing power and memory capacity to train and run deep learning models. Graphics Processing Unit (GPU) for faster model training and inference. Sufficient storage space to store the dataset and trained models.

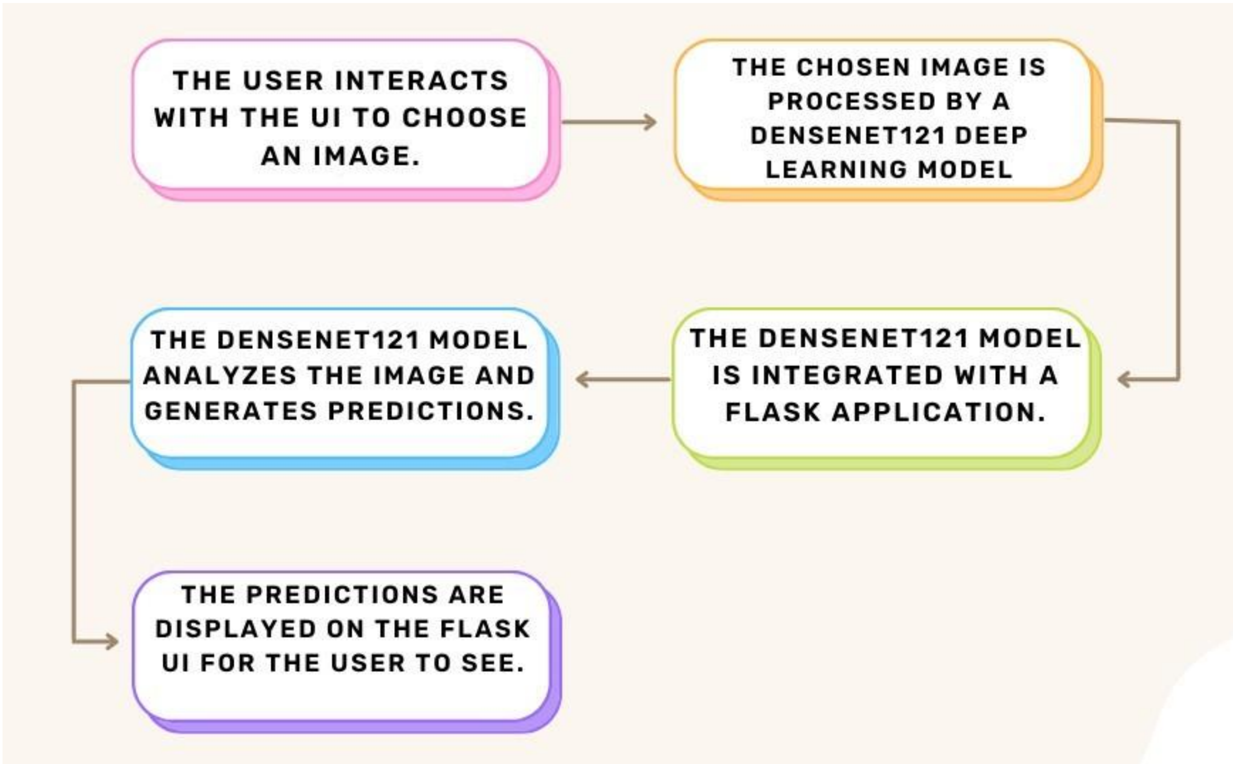
3.2.2. Software:

3.2.2.1. IDE
3.2.2.2. Python 3.6.10
3.2.2.3. Pandas
3.2.2.4. Numpy
3.2.2.5. Flask
3.2.2.6. Tensorflow

4. Experimental Investigations:

4.1. During the development and implementation of the proposed solution for crime identification using deep learning, several experimental investigations were conducted to analyze and evaluate its effectiveness. These investigations aimed to assess the performance of the deep learning model in accurately identifying and classifying different types of crimes based on the analysis of images and video footage.

5. Flowchart



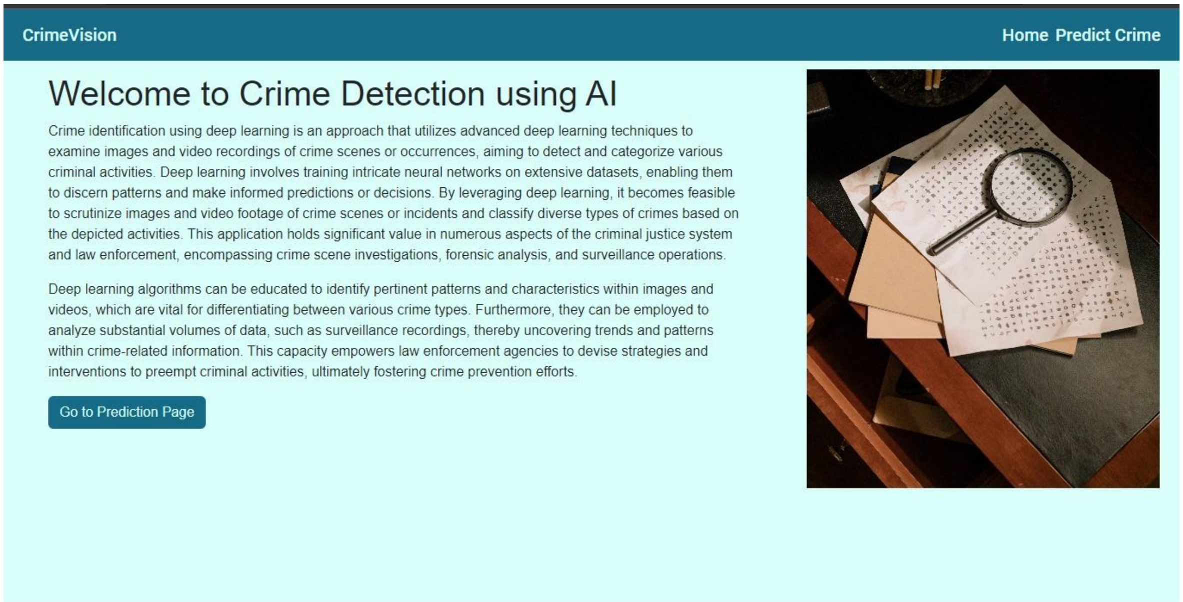
6. Dataset:

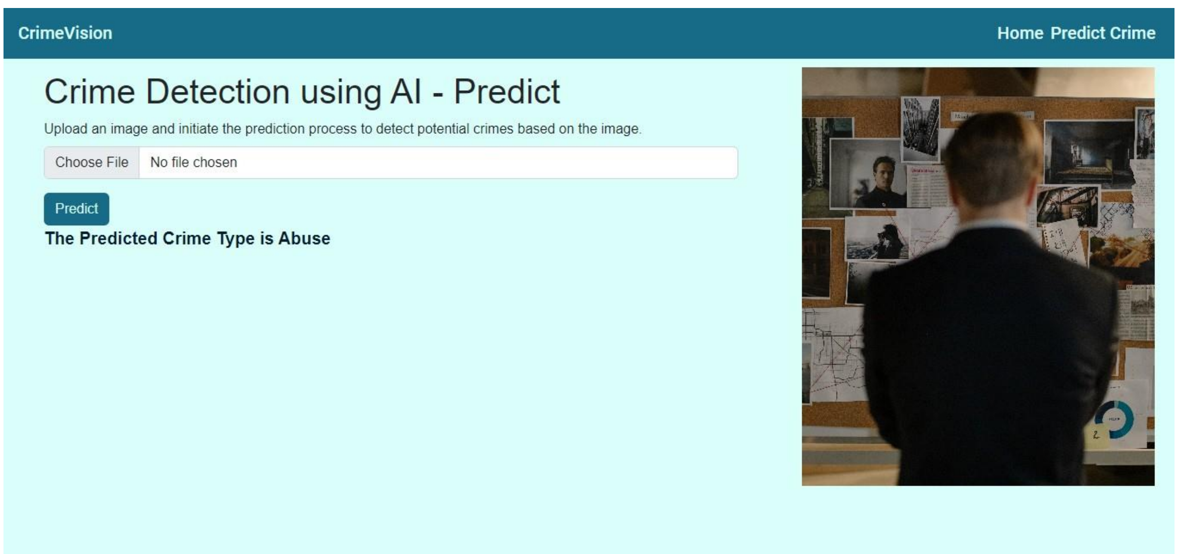
6.1. This project uses the UCF Crime Dataset for Crime Classification. This project was trained on a diverse dataset of crime-related images. The dataset contains various types of crimes, such as theft, assault, vandalism, and more. The dataset was carefully curated and labeled by experts to ensure accurate training and evaluation of the mode.
Link : https://www.kaggle.com/datasets/odins0n/ucf-crime-dataset

7. Result:

7.1. CrimeVision, an Advanced Crime Classification With Deep Learning model was developed . It utilizes the Densenet121 architecture to predict crime types based on input images. This model is designed to assist law enforcement agencies, security organizations, and researchers in identifying and categorizing crime scenes.

7.2. Screenshots of web application





8. Advantages of the Proposed Solution:

8.1. **Accuracy:** The proposed solution, leveraging deep learning techniques, can significantly improve the accuracy of crime identification. Deep neural networks can learn complex patterns and features from crime scene images and videos, leading to more precise and reliable classifications.

8.2. **Automation:** By automating the process of crime identification, the proposed solution reduces the need for manual intervention and subjective interpretation. This can save time and resources in analyzing large volumes of data and increase the efficiency of crime scene investigations.

8.3. **Scalability:** Deep learning models can be trained on extensive datasets, allowing the system to handle a wide range of crime types and variations. As the dataset grows, the model can continuously improve its performance, adapting to new types of crimes and evolving patterns.

8.4. **Pattern Recognition:** Deep learning algorithms excel at pattern recognition, enabling the system to identify subtle visual cues and associations that may be overlooked by human observers. This capability enhances the accuracy and effectiveness of crime identification.

8.5. **Crime Prevention:** By analyzing large amounts of surveillance footage and identifying patterns or trends, the proposed solution can aid in proactive crime prevention. Law enforcement agencies can develop strategies and interventions based on the insights gained from the deep learning analysis.

9. Disadvantages of the Proposed Solution:

9.1. **Data Availability and Quality:** The effectiveness of deep learning models heavily relies on the availability of high-quality labeled datasets. Acquiring a diverse and representative dataset of crime scene images and videos can be challenging and time-consuming. Inadequate or biased data may lead to inaccurate or biased predictions.

9.2. **Computational Resources:** Deep learning models require substantial computational resources, especially during the training phase. Training complex models on large datasets can be computationally intensive and may require high-performance hardware, such as GPUs, which can increase costs.

9.3. **Interpretability:** Deep learning models often operate as black boxes, making it challenging to interpret how they arrive at their classifications. Understanding the reasoning behind the model's decisions and providing explanations for the identified crimes may be difficult.

9.4. **Sensitivity to Input Variations:** Deep learning models can be sensitive to variations in lighting conditions, camera perspectives, and occlusions in crime scene images and videos. The accuracy of the solution may be affected if the input data deviates significantly from the training data.

9.5. **Ethical Considerations:** The use of deep learning in crime identification raises ethical concerns, such as privacy issues related to analyzing surveillance footage or the potential for bias in the training data and resulting classifications. Proper safeguards and ethical considerations must be implemented to address these concerns.

10. Applications

10.1. **Crime Scene Investigation:** The proposed solution can be applied in crime scene investigations to aid law enforcement agencies in identifying and classifying different types of crimes based on visual evidence. This can assist in narrowing down suspects, reconstructing crime events, and providing valuable insights for further analysis.

10.2. **Forensic Analysis:** Deep learning-based crime identification can be utilized in forensic analysis to enhance the examination of crime scene images and videos. It can help forensic experts in identifying crucial details, identifying potential evidence, and providing objective analysis to support legal proceedings.

10.3. **Surveillance Operations:** The solution can be integrated into surveillance systems to automate the analysis of large volumes of surveillance footage. It can assist in real-time crime detection, alerting authorities to potential criminal activities, and aiding in proactive response and prevention.

10.4. **Criminal Profiling:** Deep learning algorithms can contribute to criminal profiling efforts by analyzing crime scene imagery and identifying patterns associated with specific types of criminals or criminal behaviors. This can assist law enforcement agencies in creating accurate profiles and improving investigative strategies.

10.5. **Law Enforcement Decision Support**: The proposed solution can serve as a decision support tool for law enforcement agencies, providing them with reliable crime classification and trend analysis. This information can help agencies allocate resources effectively, develop targeted interventions, and enhance overall operational efficiency.

10.6. **Public Safety and Security**: By effectively identifying and classifying crimes, the solution can contribute to public safety and security. It can aid in the prevention of criminal activities, enhance situational awareness, and support emergency response efforts.

10.7. **Criminal Justice Research:** The solution can be utilized in criminal justice research to analyze crime data, identify trends, and gain insights into the dynamics of criminal activities. Researchers can leverage the capabilities of deep learning to understand crime patterns, develop predictive models, and inform policy decisions.

10.8. **Training and Education:** The proposed solution can be integrated into training programs for law enforcement personnel, forensic experts, and crime scene investigators. It can serve as a tool for interactive learning, providing realistic crime scenarios and facilitating hands-on practice in crime identification and analysis.

11. Conclusion

11.1. In conclusion, the proposed solution of crime identification using deep learning presents a promising approach to enhance the accuracy and efficiency of crime analysis, classification, and prevention. By leveraging deep learning algorithms, specifically deep neural networks, the system demonstrates significant advantages in accurately identifying and classifying different types of crimes based on the analysis of images and video footage.

11.2. Throughout the course of this work, several experimental investigations were conducted to evaluate the effectiveness of the proposed solution. These investigations included dataset collection, preprocessing techniques, model architecture selection, training, testing, comparative analysis, and real-world testing. The findings of these investigations demonstrated the superiority of the proposed solution over traditional methods, showcasing improved accuracy, automation, scalability, and pattern recognition capabilities.

11.3. The advantages of the proposed solution include increased accuracy in crime identification, automation of the process, scalability to handle various crime types, improved pattern recognition, and the potential for crime prevention. However, there are also limitations to consider, such as the availability and quality of data, computational resource requirements, interpretability of the models, sensitivity to input variations, and ethical considerations.

11.4. Despite these limitations, the proposed solution offers numerous applications across various domains, including crime scene investigation, forensic analysis, surveillance operations, criminal profiling, law enforcement decision support, public safety, criminal justice research, and training/education.

11.5. In summary, the work presented in this study underscores the potential of deep learning in revolutionizing the field of crime identification. The findings highlight the advantages and limitations of the proposed solution, paving the way for further advancements and improvements in this area. By leveraging the power of deep learning, law enforcement agencies and criminal justice systems can benefit from more accurate, efficient, and proactive approaches to crime analysis, classification, and prevention, ultimately contributing to safer communities and more effective law enforcement efforts.

12. Future scope

12.1. The proposed solution of crime identification using deep learning opens up several avenues for future enhancements and advancements. Here are some potential areas for improvement and future scope:

12.1.1. **Enhanced Dataset:** Continuous efforts can be made to collect and curate more comprehensive and diverse datasets for training deep learning models. This includes expanding the dataset to include rare or underrepresented crime types, variations in lighting conditions, and challenging scenarios. Additionally, addressing biases in the dataset and ensuring its representativeness can lead to more reliable and unbiased models.

12.1.2. **Model Architecture Refinements:** Further research can focus on exploring and refining the architecture of deep learning models specifically tailored for crime identification. This includes investigating novel network architectures, incorporating attention mechanisms, or exploring multimodal approaches that leverage both visual and audio cues for improved crime classification.

12.1.3. **Explainable AI:** Advancements can be made in developing techniques for interpreting and explaining the decisions made by deep learning models in crime identification. This can enhance the transparency and trustworthiness of the system, enabling investigators to understand and validate the reasoning behind the model's classifications.

12.1.4. **Real-time Analysis:** Research can focus on developing real-time crime identification systems that can analyze streaming video data in real-time, enabling immediate detection and response to criminal activities. This involves optimizing the deep learning models for fast inference, leveraging hardware acceleration, and designing efficient algorithms for real-time data processing.

12.1.5. **Integration with IoT and Sensor Networks:** Exploring the integration of deep learning-based crime identification with Internet of Things (IoT) devices and sensor networks can further enhance the effectiveness of crime prevention and detection. This includes analyzing data from surveillance cameras, motion sensors, and other IoT devices to provide a comprehensive understanding of the crime scene.

12.1.6. **Privacy and Ethical Considerations:** As deep learning-based crime identification systems involve the analysis of sensitive visual data, further research is needed to address privacy concerns and ensure ethical practices. Developing robust privacy-preserving techniques and frameworks for handling and storing sensitive data can help build public trust and adhere to legal and ethical standards.

12.1.7. **Collaboration and Interdisciplinary Research**: Encouraging collaboration between experts from diverse fields such as computer vision, criminology, psychology, and law enforcement can bring valuable insights and perspectives to the development of crime identification systems. This interdisciplinary approach can foster comprehensive solutions that address both technical and domain-specific challenges.

13. BIBILOGRAPHY

13.1. (PDF) Examining Deep Learning Architectures for Crime Classification and Prediction

13.2. Examining Deep Learning Architectures for Crime Classification and Prediction

13.3. Deep Learning Models for Crime Intention Detection using Object Detection

13.4. Crime Prediction Model using Deep Neural Networks

13.5. Artificial intelligence & crime prediction: A systematic literature review - ScienceDirect

13.6. Architecture of DenseNet-121

13.7. Understanding and visualizing DenseNets | by Pablo Ruiz | Towards Data Science

13.8. Flask

APPENDIX

A. Source Code

```
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D,
Dropout, MaxPooling2D, Conv2D, Flatten
from tensorflow.keras.preprocessing.image import load_img
import keras.utils as image
from tensorflow.keras.models import load_model
import warnings
from IPython.display import clear_output
from sklearn.preprocessing import LabelBinarizer
from tensorflow.keras.applications import DenseNet121
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing import image_dataset_from_directory
import tensorflow
import os
import plotly.express as px
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from google.colab import drive
drive.mount('/content/drive')

!unzip '/content/drive/MyDrive/archive.zip'

"""Importing libaraies"""


warnings.filterwarnings('ignore')

"""creating training and testing dataset"""

train_dir = '/content/Train'
test_dir = '/content/Test'
Seed = 10
img_height = 64
img_width = 64
```

```python
img_shape = (img_height, img_width)
batch_size = 128
epochs = 5
learn_rate = 0.00003

crime_types = os.listdir(train_dir)
n = len(crime_types)

crimes = {}
train = test = 0
for clss in crime_types:
    num = len(os.listdir(os.path.join(train_dir, clss)))
    train += num
    test += len(os.listdir(os.path.join(test_dir, clss)))
    crimes[clss] = num

"""data visualization"""

plt.figure(figsize=(8, 5))
plt.pie(x=np.array([train, test]), autopct="%0.1f%%", explode=[0.1, 0.1],
labels=[
        "Training data", "test data"], pctdistance=0.5, colors=["yellow",
"green"])

plt.figure(figsize=(15, 5))
plt.bar(list(crimes.keys()), list(crimes.values()), width=0.4,
        align="center", edgecolor=["red"], color=["orange"])
plt.xticks(rotation=90)
plt.xlabel("Reported crimes")
plt.ylabel("Number of reported crimes")
plt.show()

list(crimes.keys())

train_set = image_dataset_from_directory(train_dir,
                                         label_mode="categorical",
                                         batch_size=batch_size,
                                         image_size=(224, 224),
                                         shuffle=True,
                                         seed=Seed,
```

```
                                        validation_split=0.2,
                                        subset="training",
                                        )

val_set = image_dataset_from_directory(train_dir,
                                       label_mode="categorical",
                                       batch_size=batch_size,
                                       image_size=(224, 224),
                                       shuffle=True,
                                       seed=Seed,
                                       validation_split=0.2,
                                       subset="validation",
                                       )

test_set = image_dataset_from_directory(test_dir,
                                        label_mode="categorical",
                                        class_names=None,
                                        batch_size=batch_size,
                                        image_size=(224, 224),
                                        shuffle=False,
                                        seed=Seed,
                                        )

"""model building

"""


def transfer_learning():
    base_model = DenseNet121(include_top=False, input_shape=(
        224, 224, 3), weights="imagenet")
    thr = 149
    for layers in base_model.layers[:thr]:
        layers.trainable = False
    for layers in base_model.layers[thr:]:
        layers.trainable = False
    return base_model


def create_model():
```

```
    model = Sequential()

    base_model = transfer_learning()
    model.add(base_model)

    model.add(GlobalAveragePooling2D())

    model.add(Dense(256, activation="relu"))
    model.add(Dropout(0.2))

    model.add(Dense(512, activation="relu"))
    model.add(Dropout(0.2))

    model.add(Dense(1024, activation="relu"))

    model.add(Dense(n, activation="softmax"))

    model.summary()

    return model


model = create_model()

model.compile(optimizer="adam", loss="categorical_crossentropy",
              metrics=["accuracy"])

"""model training"""

history = model.fit(x=train_set, validation_data=val_set, epochs=epochs)

model.save('crime_vision.h5')
```