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Artificial Neural Networks: Build and Train a Neural Network Model for Intelligent Video Surveillance Systems

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Abstract—The statement highlights the growing concern over security across the world, particularly with the increasing advancement of technology. One of the major challenges faced is the ease with which data can be manipulated, rendering it useless to individuals who may be innocent. In response to this challenge, the proposed solution involves combining two systems, namely Closed-Circuit Television (CCTV) and Artificial Intelligence (AI), to create an advanced security system. This system is designed to detect suspicious activities and respond to them in an appropriate manner. The suggested strategy uses an artificial neural network, which can complete tasks and alert the authorities considerably more quickly than a human. By using this system, we aim to address several problems associated with the current security system. The proposed security system is expected to benefit many, reducing crime rates, and easing the burden on law enforcement authorities. Overall, the statement emphasizes the need for an improved security system that can cope with the current security challenges facing the world. It highlights the potential of integrating CCTV and AI to create an advanced security system that can be more effective in detecting and responding to suspicious activities.

Index Terms—Artificial Neural Network, Closed Circuit Tele- vision (CCTV), Artificial Intelligence (AI), security, privacy

I. INTRODUCTION

A system of video cameras, displays, and data networks called closed-circuit television (CCTV) is used to spot and deter criminal activities. For the purpose of preventing crime, video surveillance systems are utilized in both public and private settings, including public places like schools and houses. To combat crime and stop terrorism, authorities, law enforcement, and security management experts mainly rely on video surveillance. According to current estimates, there is one camera for every 13 individuals. This number includes doorbell cameras as well as cameras used for private business and public monitoring. Therefore, there is probably CCTV on your street [1]. Fundamental changes in the way digital data are collected, evaluated, shared, and stored over the past ten years have drastically changed the capabilities of surveillance cameras. The push for smarter cities and the developing industrial internet of things already heavily relies on security cameras. As cameras get better at gathering data and making predictions based on integrated analytical software firms have built, deep learning and AI are becoming more common. While the transition to a” smart home” setting is also having an impact, customers now have better access than ever to wireless devices and doorbell cameras that are simple to install [2]. A. Advantages of including artificial neural network in security camera surveillance Object detection: ANNs can be trained to detect specific objects or persons of interest, enabling security cameras to recognize and track individuals or objects in real-time. This can be useful for identifying and preventing suspicious behavior, theft, or vandalism. Intrusion detection: ANNs can be used to analyze video footage and detect unusual activity or intrusion in restricted areas. This can be especially useful in high-security areas where unauthorized access can pose a serious threat [3]. Facial recognition: ANNs can be trained to recognize faces and match them against a database of known individuals. This can be useful for identifying suspects or persons of interest in criminal investigations. Real-time monitoring: ANNs can process video data in real-time, allowing for immediate alerts and response to potential security breaches. Improved accuracy: ANNs can learn and adapt to changing environmental conditions and lighting, leading to higher accuracy and reliability in security monitoring [4]. Reduced human error: ANNs can automate the process of monitoring and analyzing video data, reducing the risk of human error and improving overall efficiency. Cost-effective: The use of ANNs in security cameras can be cost-effective as it reduces the need for additional security personnel and improves the accuracy and efficiency of security monitoring.

II. RELATED WORK

In this section, we present the survey of existing work based on intelligent video surveillance using ANN.CCTV cameras are now ubiquitous in many parts of the world and are used for a wide range of purposes, from crime prevention to traffic monitoring to industrial safety. The failure of CCTV cameras to capture important details has resulted in the inability to identify suspects or bring perpetrators to justice. Although there are several programs that offer intelligent video surveil- lance using ANN. Incorporating artificial neural networks with CCTV cameras has become a popular research topic in recent years due to its potential to enhance security systems. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have been used as major components in the construction of deep learning models for the detection of shady activity in surveillance videos. Amrutha et al. [5] developed a deep learning approach for detecting suspicious activity from surveillance video using CNNs and LSTMs. Their method achieved promising results and can be useful in security and surveillance applications where quick detection is critical. Ibrahim’s [6] paper provides a comprehensive review of intelligent surveillance systems, covering image processing, pattern recognition, and AI. The author reviews latest research, discusses challenges, and highlights future directions. For specialists in the topic, both researchers and practitioners can benefit greatly from this review. A pre-trained CNN is used by

Singh et al. [7] to extract characteristics from video frames, which are subsequently input into an unsupervised auto encoder -based system for anomaly identification. The proposed system achieves high accuracy and can be used in various applications, such as security surveillance and traffic monitoring. Islam et al. [8] analysis of the most recent video categorization techniques — including deep learn- ing and machine learning algorithms—discusses their benefits and drawbacks. The paper also highlights the challenges of video classification and provides future research directions. Zhao et al. [9] use a combination of CNNs and MLPs to extract and classify facial features from multiple views. The proposed system achieves high accuracy and can be used in various applications, such as security and surveillance. In order to recognize and categorize traffic incidents in real-time, Mandal et al. [10] present a system that makes use of deep learning algorithms, such as CNNs and LSTMs. The proposed system achieves high accuracy and can be used in various traffic management applications. Zhuang et al. [11] propose a system that uses a combination of edge computing and deep learning algorithms to detect and classify parking events in real-time. The proposed system achieves high accuracy and can be used in various parking management applications. Khan et al. [12] proposes a malware classification framework using convolutional neural networks. The authors use a pretrained CNN to extract features from malware binaries, which are then fed into a supervised classification algorithm. The proposed framework achieves high accuracy and can be used in various cybersecurity applications. Muhammad et.al [13] proposed Convolutional neural networks (CNN) based model for early fire detection. The work employed surveillance for successful disaster management. The proposed CNN-based fire detection system aims to overcome the limitations of traditional fire detection methods and provide an automated early detection system that can detect fire at its early stage during surveillance. Saxena et. al [14] The suggested CNN model outperforms con- ventional fire detection techniques, according to experimental results. The system was trained on a dataset of photos contain- ing fire and non-fire events. The research does, however, have certain drawbacks and disadvantages, such as the lack of a thorough analysis of the false positive and false negative rates of the suggested method, as well as the incomplete exploration of the interpretability and generalization aspects of the trained CNN model. Ding et al. [15] Future research can explore more diverse locations, types of fires, and additional sensory modal- ities such as audio sensation, thermal imaging, and so on. The interpretability and generalization properties of the learned CNN model can also be explored in future research. Future research can also increase the size and quality of the training and testing datasets. Wang et.al [16] reviewed recent advances in vehicle detection using deep learning, including different network architectures and datasets. It highlights challenges and limitations in the field and suggests future research directions, such as exploring more diverse scenarios and improving the interpretability and robustness of detection models. Wang et.al [17] offered a thorough analysis of the state-of-the-art approaches and most recent developments in deep learning- based pedestrian identification. It covers different difficulties and shortcomings with the current approaches and makes recommendations for future research possibilities. Lu et al [18] proposed a novel approach for object segmentation by refining object seeds using deep learning. The method consists of a two-stage refinement process, which uses a fully convolutional neural network (FCN) to generate object seeds and then refines them using a second FCN. The proposed method achieves state of-the-art performance on multiple benchmark datasets and outperforms previous state-of-the-art methods. Liu et al [19] studied the most recent deep learning techniques for super resolution of images is reviewed. Recent developments in deep learning-based techniques for single- and multiple-image super-resolution are covered, including generative adversarial networks, residual networks, and attention mechanisms. The obstacles and upcoming developments in this subject are also covered in the article. Lu, et.al [20] proposed a stereo-based autonomous landing system for a small quadrotor on a high- speed ground vehicle. The system uses a stereo camera to estimate the relative pose between the quadrotor and the ground vehicle, and a Kalman filter to estimate the state of the quadrotor. The system was evaluated through experiments, showing high accuracy and robustness in various scenarios. Chen et.al [21] presented a method for tracking human pose using a multiple-camera system. The proposed method consists of three steps: multiple-camera calibration, human detection and tracking, and human pose estimation. The experimental findings show that the proposed strategy works when applied to a dataset that was collected by a number of cameras. Zhang et.al [22] presented an intelligent video surveillance system based on deep learning for detecting anomalous events. The system comprises a pre-trained convolutional neural network (CNN) to recognize normal events and a one-class support vector machine (SVM) to detect anomalous events. The suggested system has a high level of accuracy in identifying anomalous events, making it a viable option for practical video surveillance applications. Cai et.al [23] reviewed the convolutional neural networks' use in object detection. It covers recent advances in the field, such as region-based and anchor-based methods, and discusses their strengths and weaknesses. In the review, various deep learning architectures are examined along with how they apply to object detection. Overall, the study offers a thorough summary of the state-of the-art for object detection using CNNs at this time. Zhang et.al [24] proposed a real-time video analysis system based on deep learning for surveillance purposes. The system is capable of detecting, tracking and analyzing multiple objects in a given surveillance video. A number of datasets are used to evaluate the suggested approach, and the findings are encouraging. Li et.al [25] presented a method for detecting abandoned luggage in public places using deep learning. The system is based on video analysis and achieves high accuracy in real-time detection. The article discusses the challenges of abandoned luggage detection and compares the proposed method with previous techniques. In general, the article offers information about how deep learning is used in video-based security systems [27] and [28].

III. PROPOSED METHODOLOGY

The integration of object detection and emotion detection using neural networks can significantly improve the effective- ness of surveillance cameras in detecting suspicious and dangerous activities. In our proposed methodology, we will use a combination of object detection algorithms, such as YOLOv4, and facial emotion recognition techniques, as shown in Fig 1, based on deep learning, such as VGG-16 and ResNet-50, to simultaneously detect objects and analyze the emotions of individuals captured by the camera. To implement this methodology, we will train the neural networks on large datasets of labeled images of objects and emotions, respectively. The trained models will be integrated into the surveillance camera system, which will continuously capture and analyze live video feeds. Whenever a person is detected, the emotion detection algorithm will analyze their facial expression to determine whether they are exhibiting any suspicious or dangerous behaviors, such as anger or fear. At the same time, the object detection algorithm will scan the surrounding area to identify any potential threats or objects that could be used in criminal activity. The impacts of object detection and emotion detection in surveillance cameras are numerous. Object detection can help to identify and track individuals, vehicles, and other objects of interest in real-time. It can also detect suspicious objects and movements, such as the presence of weapons or unauthorized access to restricted areas. On the other hand, emotion detection can help to analyze the behavior and intentions of individuals, by detecting their emotional state and predicting their next move. This can be particularly useful in detecting criminal activities such as theft, vandalism, or assault. Overall, the integration of object detection and emotion detection using neural networks can significantly improve the effectiveness of surveillance cameras in detecting suspicious and dangerous activities. This can lead to better security and safety for public spaces, workplaces, and other areas where surveillance cameras are deployed. 1) Collecting the dataset: In this research paper, we present a comprehensive dataset collection for object and emotion recognition in real-time image and video processing. Our dataset consists of two widely used datasets, COCO and FER 2013. COCO provides a benchmark for object detection models with over 330k images annotated with 80 different object categories. This dataset can be used to train object detection models that can recognize objects in real-time. FER 2013, on the other hand, is a dataset that contains facial expression images labeled with six different emotions. It can be used to train emotion detection models that can recognize emotions in real-time. By combining these two datasets, we provide a rich and diverse set of images and videos that can be used for object and emotion recognition tasks in various applications, such as surveillance or entertainment. Our dataset can be used to train and evaluate deep learning models that can recognize and classify objects and emotions in real-time image and video processing.

2) Refining and processing the dataset: After obtaining our dataset, the first step is to refine and process it. This involves removing any irrelevant content from the dataset and processing it multiple times to ensure that any factors not intended to be considered are not included.

Failing to do this step can result in other factors affecting our outcome. For emotion detection:-

This code loads the dataset in the form of a CSV file using Pandas library. The pixel values and labels are then extracted from the CSV file and reshaped into a 48x48 grayscale image. The labels are one-hot encoded using Pandas' get dummies () function. The train test split () function from scikit-learn is then used to divide the dataset into training and test sets.

```
# Define the neural network architecture
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(16, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])
```

Fig. 1. Processing the Emotion detection

Finally, the input shape of the images is defined as (48, 48,

1) For model training.

The provided code is used for preprocessing the images in the COCO dataset for object detection. First, the path to the dataset directory is defined, along with the directories for the training and validation sets. Next, a function called 'preprocess image' is defined to perform the actual preprocessing on each image. The function first resizes the image to 800x800 pixels, which is the size that the Faster R-CNN model used in the example is trained on. Then, the image is converted from BGR to RGB format and the pixel values are normalized to be between 0 and 1. Finally, the image is converted to a numpy array and an extra dimension is added for the batch size. This function will be called on each image in the dataset before it is fed into the model for training or testing. 3) Choosing neural network architecture: It is a critical step in the machine learning process. It's important to select an optimal architecture that can effectively understand the input data and produce the desired output. This can help simplify subsequent tasks and steps that may have been difficult otherwise.

This code defines a CNN model for emotion

detection. It has 3 Conv2D layers with increasing number of filters, followed by MaxPooling2D layers. The output is then flattened and fed into two dense layers with ReLU activation function. The number of neurons in the output layer is equal to the number of emotions that may be recognized, and softmax activation is present. Adam optimizer is used to create the model, which was trained on the Fer2013 dataset. This code defines a Convolutional Neural Network (CNN) model for detecting emotions in images. The model takes in an input image with a specific shape and passes it through a series of convolutional and pooling layers to learn features and reduce the spatial dimensions. After the final pooling layer, the output is flattened and passed through two fully connected layers with ReLU activation functions. The final layer has a number of neurons equal to the number of emotions to be detected, with a softmax activation function to output the predicted probability distribution over the emotions. The categorical cross-entropy loss function and Adam optimizer are used in the model's construction. During training, the model updates its weights to minimize the loss and improve its accuracy in predicting
the correct emotion for each input image.

This code in Fig 2. defines a Faster R-CNN model for object detection. The ResNet50 model is loaded and its layers are frozen to prevent further training. The region proposal network (RPN), which uses ResNet50's output as input and produces class probabilities and bounding box coordinates for the region proposals, is then defined. The regions suggested by the RPN are pooled by the RoI pooling layer. The fully connected layers are then defined for object detection, which take the pooled regions as input and output the final classification and regression layers. The Faster R-CNN model is then constructed by defining the inputs and outputs. The model takes two inputs, the image input and the region proposals input, and outputs four outputs, the class probabilities and bounding box coordinates of the region proposals and the final classification and regression layers. 4) Training our neural network model: Once the neural network architecture is chosen, the next step is to train the model using the dataset. This involves applying various algorithms as shown in Fig 3, both pre-existing and newly developed, to adjust the weights and biases of the neural network. These algorithms allow the neural network to learn from the input data and improve its predictions over time as shown in Fig 4. Overall, the training process is a critical step in developing an accurate and effective machine learning model. By carefully selecting and developing appropriate algorithms, and tuning the hyper parameters of the neural network, one can train the model to accurately make predictions based on input data [29-33].

5) Testing and predicting: The next stage is to test the neural network model, Fig 5 and 6, after it has been trained and a particular degree of accuracy has been attained. To do this, real-time data must be used to confirm that the predictions made by the model are accurate. One can install the model near the device or system it is intended to be used with, and observe its predictions in response to input data. In summary, testing and predicting are critical steps in the machine learning process, as they allow for the refinement and optimization of the neural network model [34-35]. By carefully analyzing its predictions and making appropriate adjustments, one can improve the overall performance of the system.

```python
# Load the dataset
dataset = tf.keras.preprocessing.image_dataset_from_directory(
    'path/to/dataset',
    labels='inferred',
    label_mode='binary',
    batch_size=32,
    image_size=(224, 224)
)

# Preprocess the input data
dataset = dataset.map(lambda x, y: (tf.image.resize(x, (224, 224)), y))
dataset = dataset.map(lambda x, y: (x / 255.0, y))
```

Fig. 2. Processing for Object detection

```python
# Define the number of emotions to detect
num_emotions = 7

# Define the model architecture
model = Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(num_emotions, activation='softmax')
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Fig. 3. Architecture of Emotion Detection

```python
# Load the pre-trained ResNet50 model and freeze its layers
resnet = ResNet50(weights='imagenet', include_top=False, input_shape=input_shape)
for layer in resnet.layers:
    layer.trainable = False

# Define the region proposal network (RPN)
rpn = tf.keras.layers.Conv2D(256, (3, 3), padding='same', activation='relu')(resnet.output)
rpn_class = tf.keras.layers.Conv2D(2, (1, 1), activation='softmax', name='rpn_class')(rpn)
rpn_bbox = tf.keras.layers.Conv2D(4, (1, 1), activation='linear', name='rpn_bbox')(rpn)

# Define the RoI pooling layer
roi_input = tf.keras.layers.Input(shape=(None, 4))
pooled_regions = tf.keras.layers.RoiPoolingConv(7, 1/16)([resnet.output, roi_input])

# Define the fully connected layers for object detection
flatten = Flatten()(pooled_regions)
fc1 = Dense(1024, activation='relu')(flatten)
fc2 = Dense(1024, activation='relu')(fc1)

# Define the final classification and regression layers
class_output = Dense(num_classes, activation='softmax', name='class_output')(fc2)
bbox_output = Dense(num_classes * 4, activation='linear', name='bbox_output')(fc2)

# Define the Faster R-CNN model
model = Model(inputs=[resnet.input, roi_input], outputs=[rpn_class, rpn_bbox, class_output, bbox_output])
```

Fig. 4. Architecture of Object Detection

```
# Split the dataset into training and testing sets
train_dataset = dataset.take(800)
test_dataset = dataset.skip(800)

# Define the loss function and optimizer
loss_fn = tf.keras.losses.BinaryCrossentropy()
optimizer = tf.keras.optimizers.Adam()

# Train the model
model.compile(loss=loss_fn, optimizer=optimizer, metrics=['accuracy'])
model.fit(train_dataset, epochs=10)
```

Fig. 5. Training Dataset

```
# Evaluate the model
model.evaluate(test_dataset)

# Save the model
model.save('path/to/model')
```

Fig. 6. Evaluating model

IV. RESULT

Convolutional neural networks (CNNs), in particular, are efficient tools for creating such systems, according to the study paper's findings on the construction and training of a neural network model for intelligent video surveillance systems. The paper highlights the importance of providing large datasets of labeled video frames for the network to learn patterns and features associated with different classes of objects and events. The trained neural network model can be used for various applications in video surveillance systems, including object detection, tracking, and activity recognition. However, a number of variables, such as the caliber of the video data input, the complexity of the scene, and the precision of the labelling process, affect how well the system performs. With advances in technology and the availability of large datasets, we can expect further improvements in the performance of these systems in the future.

This graph in Fig 7 and Fig 8 tells us the combined result of emotion and object detection and based on that it gives accuracy about whether the model is detecting suspicious activity correctly or not.

This graph tells us the combined result of emotion and object detection and based on that it gives loss about how far are the real result from the expected result in correct detection of suspicious activity.

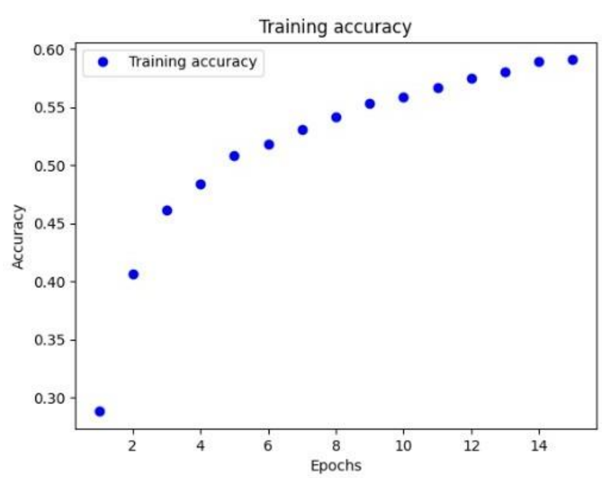

Fig. 7. Accuracy Graph

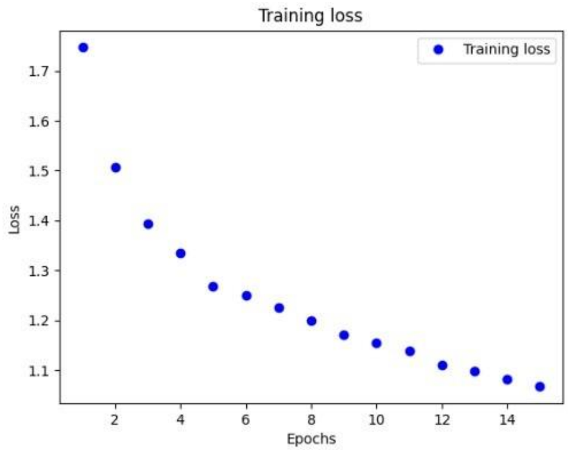

Fig. 8. Loss Graph

V. CONCLUSION

The study paper concludes that Convolutional Neural Net- works (CNNs) are effective in the development of intelligent video surveillance systems. The study emphasizes the importance of furnishing extensive datasets comprising an- notated video frames to facilitate the network's acquisition of patterns and characteristics linked to diverse objects and occurrences. The utilization of neural network models can enable the achievement of multiple applications, including object detection, tracking, and activity recognition, in video surveillance systems through training.

The efficacy of said systems is contingent upon multiple variables, such as the caliber of the video data input, intricacy of the scene, and precision of the labelling procedure. These variables have a direct influence on the system's precision in identifying dubious behavior.

The paper depicts an accuracy graph that integrates the outcomes of both emotion and object detection, offering a metric for the model's efficacy in identifying questionable behavior. It denotes the precision of the system in accurately detecting said activities. Furthermore, the graphical representation of loss (Figure 8) highlights the discrepancy between actual and anticipated outcomes in the context of identifying dubious behavior. It quantifies the extent of deviation from the expected result. Anticipated progress in technology and the increased accessibility of extensive datasets are projected to augment the efficacy of intelligent video surveillance systems. With the ongoing evolution of these systems, it is expected that there will be enhancements in the precision, resilience and effectiveness of identifying and averting dubious actions in practical situations.

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