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Weapon Detection System Using Deep Learning

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ABSTRACT

The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself. CNN is also computationally efficient. Due to its high recognition rate and fast execution, the convolutional neural networks have enhanced most of computer vision tasks, both existing and new ones. In this article, we propose an implementation of traffic signs recognition algorithm using aconvolution neural network. Weapon detection systems using deep learning have shown promising results in detecting firearms and other dangerous objects in surveillance videos and images. These systems have the potential to improve public safety by providing realtime alerts to law enforcement agencies in situations where weapons are present. However, there are still challenges to be addressed, such as the need for largescale training data, the potential for false positives and negatives, and the ethical considerations surrounding the use of these systems. Further research and development are needed to improve the accuracy and reliability of weapon detection systems and to ensure their responsible deployment in real-world settings.

Keywords: Weapon, CNN, Deep learning.

INTRODUCTION

1.1 AIM OF THE PROJECT

Security Enhancement: The primary goal is to improve security by implementing an automated weapon detection system that can quickly and accurately identify potential threats in real-time. Public Safety: Creating a safer environment for the public by reducing the risk of violence or criminal activities involving weapons. Early detection can lead to prompt responses and prevent potential harm.

1.2 SCOPE OF THE PROJECT

Deep Learning Models: Selection of appropriate deep learning architectures for weapon detection, such as convolutional neural networks (CNNs) or object detection models like. Training the model with a diverse dataset that includes various types of weapons, angles, lighting conditions, and backgrounds. Data Collection and Preparation: Collection of a comprehensive dataset containing images or videos with instances of weapons. Pre-processing and augmentation of data to enhance the model's ability to generalize to different scenarios.

1.3 OBJECT OF THE PROJECT

Develop Deep Learning Model: Design and develop a robust deep learning model for the automatic detection of weapons in images or videos. Accurate Detection: Achieve a high level of accuracy in weapon detection to minimize false positives and negatives, ensuring reliable results in real-world scenarios.

1.4 SIGNIFICANCE:

The Weapon Detection System holds significant importance in augmenting security measures across a spectrum of public spaces, including airports, schools, transportation hubs, and crowded events. The project aims to contribute to the reduction of response times to potential threats, thereby minimizing the risk of violence and enhancing overall public safety.

1.5 INTRODUCTION

Security Enhancement: The primary goal is to improve security by implementing an automated weapon detection system that can quickly and accurately identify potential threats in real-time. Public Safety: Creating a safer environment for the public by reducing the risk of violence or criminal activities involving weapons. Early detection can lead to prompt responses and prevent potential harm. Automation and Efficiency: Developing a system that automates the process of weapon detection, reducing the reliance on human surveillance and increasing the efficiency of security measures.

LITERATURE SURVEY

1. N. Kurek, L. A. Darzi and J. Maa, "A Worldwide perspective provides insights into why a US surgeon-general annual report on firearm injuries is needed in America," Current Trauma Reports,vol.6, pp.36–43, 2020.

The review aims to empower the USA to better understand the myriad reasons that contribute to nearly40,000 firearm deaths and over 100,000 gun injuries estimated annually. By examining global insights and preventive approaches utilized around the world for tackling this growing public health threat, it aims to highlight why a US Surgeon General Annual Report on firearm injuries is needed. Recent Findings The review summarizes themes in the worldwide experience with firearm injuries and explores the challenge from the perspective of Japan, Honduras, Brazil, India, and Germany.

2. Y. Ren, C. Zhu and S. Xiao, "Small object detection in optical remote sensing images via modified faster R-CNN," Applied Sciences, vol. 8, no. 5, pp. 813– 818, 2018.

The PASCAL VOC Challenge performance has been significantly boosted by the prevalently CNN-based pipelines like Faster R-CNN. However, directly applying the Faster R-CNN to the small remote sensing objects usually renders poor performance. To address this issue, this paper investigates on how to modify Faster R-CNN for the task of small object detection in optical remote sensing images. First of all, we not only modify the RPN stage of Faster R-CNN by setting appropriate anchors but also leverage a single high-level feature map of a fine resolution by designing a similar architecture adopting top-down and skip connections.

3. R. Olmos, S. Tabik and F. Herrera, "Automatic handgun detection alarm in videos using deep learning," Neurocomputing, vol. 275, no. 9, pp. 66– 72, 2018.

Current surveillance and control systems still require human supervision and intervention. This work presents a novel automatic handgun detection system in videos appropriate for both, surveillance and control purposes. We reformulate this detection problem into the problem of minimizing false positives and solve it by building the key training data-set guided by the results of a deep Convolutional Neural Networks (CNN) classifier, then assessing the best classification model under two approaches, the sliding window approach and region proposal approach.

4. M. M. Ghazi, B. Yanikoglu and E. Aptoula, "Plant identification using deep neural networks viam optimization of transfer learning parameters," Neurocomputing, vol. 235, no. 7, pp. 228–235, 2017.

We use deep convolutional neural networks to identify the plant species captured in a photograph and evaluate different factors affecting the performance of these networks. Three powerful and popular deep learning architectures, namely GoogLeNet, AlexNet, and VGGNet, are used for this purpose. Transfer learning is used to fine-tune the pre-trained models, using the plant task datasets of LifeCLEF 2015. To decrease the chance of overfitting, data augmentation techniques are applied based on image transforms such as rotation, translation, reflection, and scaling.

5. X. Shu, Y. Cai, L. Yang, L. Zhang and J. Tang, "Computational face reader based on facial attribute estimation," Neurocomputing, vol. 236, no. 10, pp. 153–163, 2017.

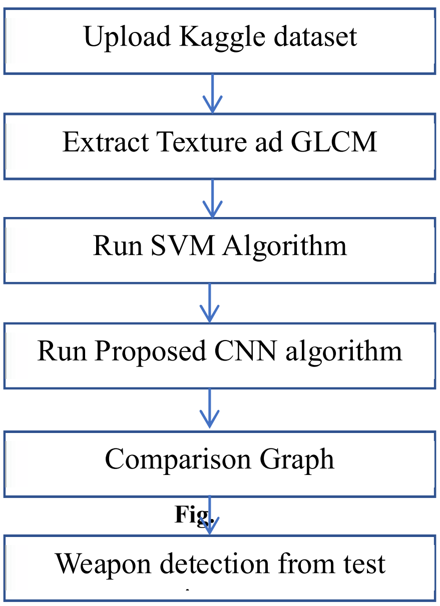
Chinese face reading has demonstrated the often satisfying capabilities to tell the characteristics (mostly exaggerated as fortune) of a person by reading his/her face, i.e. understanding the fine-grained facial attributes (e.g., length of nose, single/double-fold eyelid, density of eyebrows, etc.). Thus, a smart face reading system should estimate the fine-grained facial attributes well. Therefore, In this paper, we first study the fine-grained facial attribute estimation problem and propose a novel deep convolutional network equipped with a new facial region pooling layer (called FRP-net), to accurately estimate the fine-grained facial attributes. To capture the characteristics of fine-grained facial attributes, the embedded FRP layer implements the pooling operation on the searched facial region windows (locates the region of each facial attribute) instead of the commonly-used sliding windows.

PROPOSED METHOD

CNN Models:

In object recognition applications, the most used deep learning algorithm is the CNN algorithm. This algorithm showed outstanding success in the ImageNet Large-Scale Visual Recognition Competition held in 2012 and has been used in the development of new models in many areas since then .

Flowchart for proposed methodology is as shown below,



3.4 Flowchart

RESULT

To run project double click on ‘run.bat’ file to get below screen

Fig5.1.Run. Bat file

In above screen click on ‘Upload Kaggle Dataset’ button to upload dataset and then will get below output

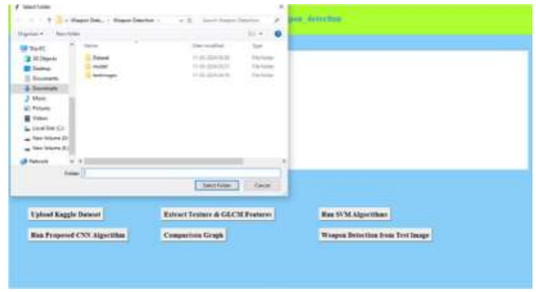


Fig5.2 Upload Kaggle Dataset

In above screen selecting and uploading entire Dataset folder and then click on ‘Select Folder’ button to load dataset and then will get below output

Fig5.3 Extract texture and GLCM features

In above screen questions, answers and images dataset loaded and now click on ‘Extract texture and GLCM features’ button to extract features from questions and image and then will get below output

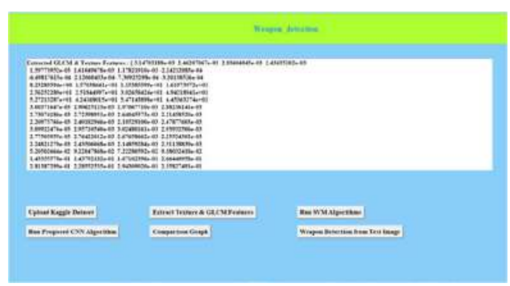


Fig.5.4 Run SVM algorithm

In above screen rum SVM algorithm we get confusion matrix and accuracy for SVM,

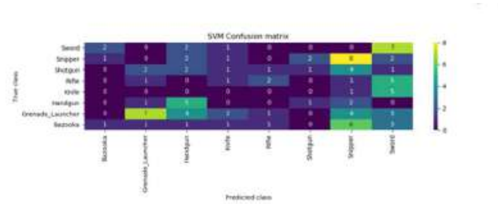


Fig.5.4 SVM confusion matrix

Fig.5.5 Accuracy for SVM

In above screen click on proposed CNN algorithm, below is the confusion matrix

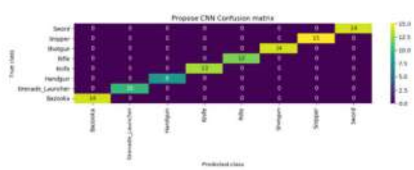


Fig.5.6 Proposed CNN confusion matrix

In below screen we can see accuracy for CNN

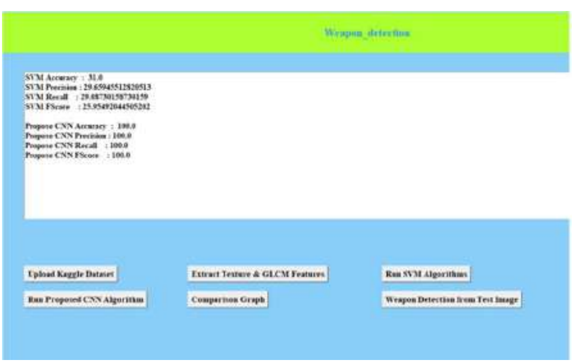


Fig.5.7 Accuracy for CNN

In below screen we can see the comparison graph of SVM and CNN

Fig.5.8 Comparison graph for SVM and CNN

And finally select the weapon detection from test image, we get below screen

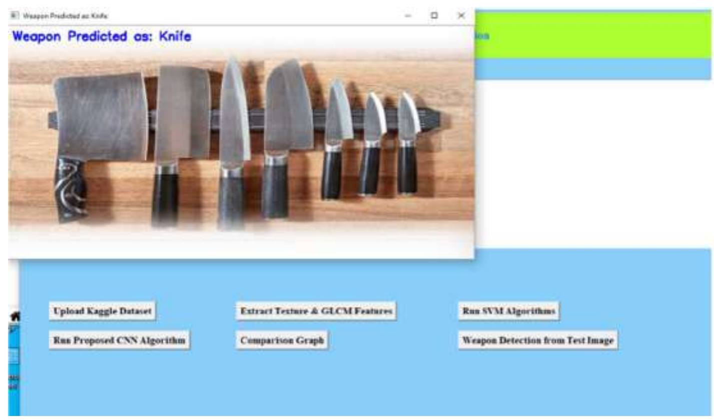


Fig.5.9 weapon detection form test image

Similarly we can check for another image

CONCLUSION

The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself. CNN is also computationally efficient. Due to its high recognition rate and fast execution, the convolutional neural networks have enhanced most of computer vision tasks, both existing and new ones. In this article, we propose an implementation of traffic signs recognition algorithm using a convolution neural network. Weapon detection systems using deep learning have shown promising results in detecting firearms and other dangerous objects in surveillance videos and images. These systems have the potential to improve public safety by providing realtime alerts to law enforcement agencies in situations where weapons are present. However, there are still challenges to be addressed, such as the need for largescale training data, the potential for false positives and negatives, and the ethical considerations surrounding the use of these systems. Further research and development are needed to improve the accuracy and reliability of weapon detection systems and to ensure their responsible deployment in real-world settings.

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