International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 10 Issue 4 ǁ 2022 ǁ PP. 35-38

Image Colorizer- an application of ComputerVision

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Abstract
Computer vision is a branch of artificial intelligence (AI) that allows computers and systems to extract useful information from digital pho- tos, videos, and other visual inputs, as well as to conduct actions or make recommendations based on that data. If artificial intelligence al- lows computers to think, computer vision allows them to see, watch, and comprehend.
Human vision is similar to computer vision, with the exception that people have a head start. Human vision benefits from lifetimes of con- text to teach it how to distinguish objects apart, how far away they are, whether they are moving, and whether something is incorrect with an image.

Date of Submission: 01-04-2022 Date of acceptance: 14-04-2022

I. Introduction

Computer vision teaches computers to execute similar tasks, but using cameras, data, and algorithms rather than retinas, optic nerves, and a visual cortex, it must do it in a fraction of the time. Because a system trained to check items or monitor a production asset can assess hundreds of products or processes per minute, detecting faults or issues that are invisible to humans, it can swiftly outperform humans[1].

What is computer vision and how does it work

A lot of data is required for computer vision. It repeats data analysis until it detects distinctions and, eventually, recognizes images[2]. To teach a computer to recognize automotive tires, for example, it must be fed a large number of tire photos and tire-related materials in order for it to understand the differences and recognize a tire, particularly one with no faults[3].

To do so, two key technologies are used: DEEP LEARNING, a sort of machine learning, and a convolutional neural network (CNN).

Machine learning is a technique that allows a computer to train itself in the context of visual input using algorithmic models. If enough data is supplied into the model, the computer will ”look” at the data and learn to distinguish betweenimages[4]. Instead of someone training the machine to recognize an image, algorithms allow it to learn on its own.By breaking images down into pixels that are given tags or labels, a CNN aids a machine learning or deep learning model in ”seeing.” It creates predictions about what it’s ”seeing” by using the labels to do convolutions (a mathematical operation on two functions to produce a third function). In a series of iterations, the neural network executes convolutions and assesses the accuracy of its predictions until the predictions start to come true. It then recognizes or sees images in a human-like manner[5].

Like a human recognizing a picture from a distance, a CNN detects hard edges and simple forms first, then fills in the details as it runs iterations of its predictions. To comprehend single images, a CNN is employed. In video appli- cations, a recurrent neural network (RNN) is used similarly to help computers grasp how visuals in a sequence of frames are related to each other.

Development of computer vision

For nearly 60 years, scientists and engineers have been attempting to find ways for robots to comprehend and analyze visual input. In 1959, physiologists pre- sented a cat with a series of images to see if it could correlate with a response in its brain. They noticed that it initially responded to hard edges or lines, imply- ing that image processing begins with simple shapes such as straight edges[6].

The first computer image scanning technology was created simultaneously, allowing computers to digitize and acquire images. In 1963, computers convertedtwo-dimensional images into three-dimensional forms, marking yet another mile- stone. AI became an academic topic of research in the 1960s, and it was alsothe start of AI's attempt to address the human vision problem.

Optical character recognition (OCR) technology was introduced in 1974, and it could recognize text printed in any font or typeface. Similarly, neural networks could be used to decipher handwritten text using intelligent character recognition (ICR). OCR and ICR have since made their way into document and invoice processing, vehicle plate recognition, mobile payments, machine translation, and various other applications.

David Marr, a neuroscientist, discovered that vision was hierarchical in 1982 and developed algorithms for robots to detect edges, corners, curves, and other essential structures. Kunihiko Fukushima, a computer scientist, devised a net- work of cells that could recognize patterns simultaneously. Convolutional layers in a neural network were used in the Recognition network[7].

By 2000, the research focus had shifted to object recognition, and the first real-time face recognition applications were developed in 2001. Throughout the 2000s, standardization of how visual data sets are labelled and annotated arose. The ImageNet data set was released in 2010. It comprised millions of annotated photos from a thousand different object classes and served as the basis for today's CNNs and deep learning models. In 2012, a team from the Universityof Toronto competed in an image recognition competition with a CNN. The model, dubbed AlexNet, drastically lowered picture identification error rates. Error rates have dropped to just a few percent since this breakthrough.

Uses of computer vision

Many firms lack the financial means to establish computer vision laboratories and develop deep learning models and neural networks. They may also be un- able to handle large amounts of visual input due to a lack of computer capability. IBM, for example, is assisting by providing computer vision software develop- ment services. These services provide cloud-based pre-built learning models while also reducing the demand on computing resources. Users use an appli- cation programming interface (API) to access to the services and use them tocreate computer vision applications.

In addition, IBM has released a computer vision platform that covers both development and computational resource constraints. Without coding or deep learning knowledge, subject matter professionals can label, train, and deploy deep learning vision models with IBM Maximo Visual Inspection. Local data centres, the cloud, and edge devices can all use the vision models.

While obtaining resources to develop computer vision apps is becoming eas- ier, an essential issue to address early on is: What will these applications do? Understanding and defining unique computer vision tasks can help to focus and evaluate projects and applications, as well as make getting started easier.

computer vision challenges

When a dog, an apple, or a person's face is seen, image classification can clas- sify it. It can accurately identify whether or not a particular image belongs toa specific class. A social network firm, for example, would want to utilise it to automatically detect and separate problematic photographs shared by users.

Object detection can employ image classification to identify a certain image class before detecting and tabulating their appearance in an image or video. Detecting damage on a manufacturing line or spotting machinery that requires repair are two examples.

Object tracking is the process of following or tracking an object after ithas been detected. This task is frequently carried out using sequenced photos or real-time video streams. For example, autonomous vehicles must not only identify and detect items like pedestrians, other automobiles, and road infras- tructure, but also track them in motion to avoid crashes and follow traffic laws.

Computer vision is used in content-based image retrieval to browse, search, and retrieve photos from massive data repositories based on the content of the images rather than metadata tags. This task could include automatic image annotation, which would take the role of manual image tagging. These tasks can be used to digital systems to improve search and retrieval accuracy.

Applications for computer vision

In the discipline of computer vision, there is a lot of work being done, but it isn't all research. Computer vision is critical in business, entertainment, transportation, healthcare, and everyday life, as demonstrated by real-world applications. The deluge of visual information streaming from smartphones, security systems, traffic cameras, and other visually instrumented devices is a primary driver for the expansion of these applications. This information might be extremely useful in a variety of businesses, but it is currently underutilised. The data serves as a training ground for computer vision

applications as wellas a launchpad for them to integrate into a variety of human activities:
For the 2018 Masters golf event, IBM employed machine vision to produce My Moments. After watching hundreds of hours of Masters film, IBM Watson was able to recognise the sights (and sounds) of key scenes. These pivotal moments were chosen and distributed to viewers as individual highlight clips.
With Google Translate, users can aim their smartphone camera at a sign in another language and get a translation in their favourite language practically instantly.

Computer vision is used in the development of self-driving automobiles to interpret the visual input from the car's cameras and other sensors. Other au- tomobiles, traffic signs, lane markers, pedestrians, bicycles, and all other visual information seen on the road must all be identified.
With partners like Verizon, IBM is bringing sophisticated AI to the edge andassisting automobile makers in identifying quality flaws before a vehicle leaves the factory[8].

ImageColorizer

The unique approach we'll employ today is based on deep learning. We'll usea Convolutional Neural Network to colorize black-and-white photographs with results that can even "deceive" people! Instead, the unique approach we'll em- ploy today is based on deep learning. A Convolutional Neural Network capable of colorizing black and white photos will be used.

Figure 1: Black and White Image

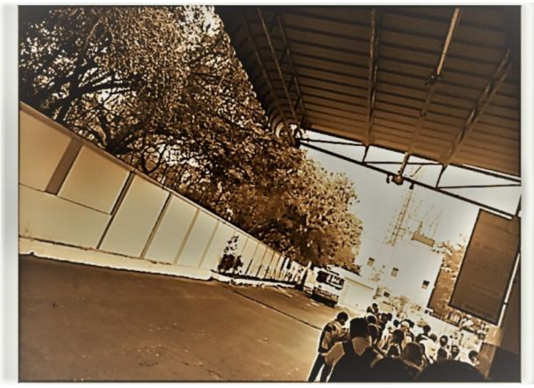

Figure 2: Colored image after using computer vision

II. Conclusion

Number of applications in day to day life uses CNN like image classification, facial recognition, speech recognition etc. Facial Recognition uses CNN for identifying faces from the picture by edge detection.In this paper we have uses the colorization algorithm of computer vision.

References

[1]. Laith Alzubaidi, Jinglan Zhang, Amjad J Humaidi, Ayad Al-Dujaili, Ye Duan, Omran Al-Shamma, J Santamar´ıa, Mohammed A Fadhel, Muthana Al-Amidie, and Laith Farhan. Review of deep learning: Con- cepts, cnn architectures, challenges, applications, future directions. *Journal of big Data*, 8(1):1–74, 2021.

[2]. Samuel Clark, Ehsan Kamalinejad, Christian Magpantay, Suritaneil Sahota,Jiaofei Zhong, and Yanke Hu. A review of cnn on medical imaging to diag- nose covid-19 infections. In *Proceedings of ISCA 34th International Confer-ence on*, volume 79, pages 91–98, 2021.

[3]. Sunanda Gamage and Jagath Samarabandu. Deep learning methods in net- work intrusion detection: A survey and an objective comparison. *Journal of Network and Computer Applications*, 169:102767, 2020.

[4]. Sorin Grigorescu, Bogdan Trasnea, Tiberiu Cocias, and Gigel Macesanu. A survey of deep learning techniques for autonomous driving. *Journal of Field Robotics*, 37(3):362–386, 2020.

[5]. Andreas Kamilaris and Francesc X Prenafeta-Boldú. A review of the use of convolutional neural networks in agriculture. *The Journal of AgriculturalScience*, 156(3):312–322, 2018.

[6]. Teja Kattenborn, Jens Leitloff, Felix Schiefer, and Stefan Hinz. Review on convolutional neural networks (cnn) in vegetation remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 173:24–49, 2021.

[7]. Gaurav Tripathi, Kuldeep Singh, and Dinesh Kumar Vishwakarma. Convo- lutional neural networks for crowd behaviour analysis: a survey. *The VisualComputer*, 35(5):753–776, 2019.

[8]. Xiu-Shen Wei, Jianxin Wu, and Quan Cui. Deep learning for fine-grained image analysis: A survey. *arXiv preprint arXiv:1907.03069*, 2019.