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Technology for Viticulture Using Computer Vision and Machine Learning

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ABSTRACT:-

Introduction :- The capacity to solve machine intelligence issues in their entirety is a result of the field of artificial intelligence's (AI) progress. Recently, the direct training of computers with minimal human contact has led to the rise in popularity of machine learning (ML). In today's world, the machine will learn automatically, replacing the previous situation of hand feeding. Features like feature extraction, pattern recognition, object identification, and classification are among the specific uses for supervised and unsupervised machine learning approaches.

OBJECTIVES:- ML is a key component of Computer Vision (CV) that helps to extract important information from pictures. Numerous fields, including robotics, optical character recognition, surveillance systems, suspect detection, and many more, benefit from CV's excellent contributions. The field of CV research is moving toward the healthcare sector. Medical imaging (MI) is a new technology that is essential to improving picture quality and identifying important characteristics of binary medical images. It also helps to mask the original image into grayscale and sets threshold values for segmentation.

CONTRIBUTION:- This paper will discuss the state-of-the-art, machine learning, and its application to computer vision and image processing. The types of tools and applications, datasets, and approaches will all be covered in detail by this survey. Future work problems and past job limitations were also explored. In order to effectively apply machine learning (ML) to computer vision and image processing, we also identify and explore a number of unresolved difficulties that still need to be resolved.

METHODS, RESULTS, AND CONCLUSION: This review paper has covered a variety of supervised and unsupervised machine learning techniques and algorithms, as well as a general overview of image processing and its impact on results. It also discusses neural network-enabled models, tools, and applications for CV, as well as important areas of open research for machine learning in CV.

Keywords:- Machine Learning, Computer Vision, Supervised and Unsupervised Learning, Medical Imaging, Pattern Recognition, Feature Extraction, Neural Network.

Introduction :- AI is a broad discipline that is now gaining popularity throughout the globe. Some academics define AI as "a system that thinks like humans" [1], while others refer to it as "a system that acts like humans" [2]. AI can change depending on a certain environment; it lacks a formal justification [3]. Although strong and weak artificial intelligence differ slightly, it is nevertheless important in many areas of computer technology. Machine intelligence can assess the two primary facets of artificial intelligence, according to Keng Siau et al.: "Weak only focus on the narrow task and strong targets more than one area" [4]. The most well-known example of an artificial intelligence crawler search (content-based search mechanism) is Google, along with a number of active implementations in different contexts. In the realm of gaming technology, Deep Blue Machine is an artificial intelligence software that has defeated world chess champion Garry Kasparov in a string of six-game matchups [5]. The computer may autonomously make an appropriate judgment (test) after learning automatically (train) from a provided dataset [6]. Millions of unique records make up the dataset, which is the primary important milestone in machine learning [7]. There are two primary forms for data: qualitative and quantitative. While quantitative data consists of numerical records that may be examined for statistical analysis, qualitative data is gathered through written documents, observations, and interviews [8, 9, 10]. Qualitative refers to a machine's ability to identify various item shapes, colors, sizes, weights, models, etc. Three key learning approaches may be categorized under machine learning (ML): semi-supervised learning (SSL), supervised learning (SL), and unsupervised learning (USL). SL is a prediction tool that uses labeled training data. Supervised learning encompasses classification and regression, with common methods including Support Vector Machine (SVM), KNN, logistic regression, Decision tree, and random forest [11]. To extract features from the input data, USL uses unlabeled training data on the other end [12].

A collection of related records or data is referred to as a cluster, and it is an unsupervised process. When we discuss clustering algorithms, K-mean is the first method that comes to mind. However, there are other options as well, such as DBSCAN and hierarchical clustering. Finally, SSL is a result of the cooperation of USL and SL. It is mostly utilized in bio-information retrieval, image processing, and information retrieval. It contains a significant number of unlabeled data in addition to a modest amount of labelled data [12]. Using classification to label the data, we first apply clustering to an unlabeled dataset in order to group the same data.
Continuity, cluster, and manifold assumptions are the preferred algorithms. Last but not least, SSL is the result of the cooperation of SL and USL. It mostly serves information retrieval, image processing, and bio-information with a significant number of unlabeled data and a limited amount of labelled data [13]. In this procedure, we first use clustering on an unlabeled dataset to group identical data after classifying those data. The manifold, cluster, and continuity assumptions are the preferred algorithms.
In 1960, Larry Roberts, the founder of computer vision, suggested in his MIT doctoral thesis the extraction of 3D geometrical information from 2D perspectival polyhedral ideas [13]. This marked the beginning of the field of computer vision. In the first phase, CV demonstrates the use of computer models to extract important information from digital photographs. Defining dual objectives, vision is employed as an autonomous system for engineering perspectives, much as a human may execute a visual task, and computational models are utilized in the human biological system to identify bodily sickness signs [14]. From an engineering standpoint, CV has been effectively used in a learning environment where students' attendance is obtained through the use of attendance tracking devices. automatically using facial recognition and detection using a camera [15]. Unmanned Aerial Vehicle (UAV) is a vision-based agent that operates without a human pilot to monitor undesirable situations. A survey paper on the most recent advancements and uses of UAV systems was written by Kanellakis et al. [16]. Within the biological setting, medical imaging (MI) is a young discipline with a growing amount of research being conducted for the benefit of society every day. The goal of MI is to extract pertinent information from medical pictures, however as time goes on, poor image quality might provide new difficulties for researchers. In the innovation age, Kesner et al. emphasize the ideas of digitizing and using MI data [17]. Maintaining expert annotation through automatic extraction of tagged images from radiological reports using natural language processing is an expensive procedure known as MI [18]. Author Alan Alexander et al. established the future course of MI in 2021 in a recent research published by McKinsey and Company, New York, USA. They said that the important components of next blockchain innovations will be the technological

cluster growth rate, cutting edge practice, and implications [19]. However, there are a few key areas where technology excels and they are covered below:

• From an agricultural perspective, robot farming employing CV and ML algorithms to boost output while maintaining quality.
Face innumerable restrictions related to agriculture, such as those related to item size, color, texture, and reflectivity [20].
• Although there are many applications and studies on handwritten and recorded script text identification, real-time picture detection, such as street view images, and accurate character recognition in images continue to be a growing challenge for machine learning [21].
• One of the drawbacks of machine learning (ML) is its limited number of picture datasets; successful training and testing can only be achieved with a vast quantity of labeled or unlabeled data.

This paper will discuss the state of the art, machine learning, deep learning, and computer vision and image processing applications of machine learning. Information on the kinds of tools and applications, datasets, and methodologies will be provided via this survey. Future work difficulties and the limitations of past work were also considered. In addition, we list and address a number of unresolved problems that need to be fixed before machine learning may be effectively applied to computer vision and image processing.
The work is divided into eight sections, the second of which is devoted to image processing using machine learning approaches. The intricacies of neural network models are covered in Section 3, tools and applications are covered in Section 4, and datasets for computer vision and image processing are covered in Section 5. In a similar vein, sections 6 and 7 discuss the difficulties and constraints facing machine learning research provides open research issues for future work. Finally, in section 8 we conclude this review paper.

2. Image Processing Methods Using Machine Learning

To process an image using a digital computer is to engage in image processing (IP). Building upon this technology, techniques for improved image quality may be used to important details from the picture should be extracted [22, 23]. An equivalent method and digital image processing (DIP) method are the two primary types [24, 25]. When using IP, the system receives input in the form of an image and gets the output in the same format. making reference to the three crucial IP components that are covered below:
• begin with the process of acquiring images.
• Adjusting and evaluating the picture
• Output that takes the shape of a picture and is determined by analysis
Everything is stored in binary format on a digital computer. Images are stored as raster pixels, where each pixel represents a numeric value from a two-dimensional array (x being row and y being column, for example). Analog IP allows for the application of processing to printable images, where pictures are any hard copies. Basic visual analysis methods are used to examine the image. In contrast, DIP manipulates digital pictures by only adhering to three fundamental principles: (i) pre-processing; (ii) enhancing; and (iii) extracting the information presented on a digital computer [26].
The initial phase in the IP process is image acquisition, which involves applying a scale (converting RGB to grayscale) to a loaded picture [27, 28]. The input image might have hidden details extracted with the use of image enhancing techniques. Based on a probabilistic or mathematical model, image restoration addresses deterioration. IP also includes color image processing, which manages the IP's color model (full color and pseudo-color). Images from different degrees are checked using wavelets and multi-resolution processing [29]. This is referred to as compression once the image's resolution, size, and completion angle have been adjusted.
One of the essential stages of IP is morphological processing, which extracts component information and delivers it to the segmentation phases, which divide the image into objects (segmenting an independent picture is a challenging problem) [30, 102]. These objects are representations of the transformed processed data from the segmentation solution space [30, 103]. Ultimately, things that are used in further processing are assigned a label via object detection and

recognition. Digitization in DIP refers to the process of transforming a continuous image or video signal into a digital image. Digitization is only possible when the image function (x, y) is digitized in both spatial and amplitude dimensions. To sample something is to collect a sample and ascertain its spatial resolution picture, sampling consists of two primary steps: (I) up sampling and (ii) down sampling [31]. Because to noise, the signal varies at random times. Obtaining additional samples is the process of decreasing noise in sampling [32]. The level of quantization is determined by the amount of gray in the scale, and it works in the opposite way from sampling (digitizing the amplitudes) [31]. The following paragraphs will go into additional detail about the three primary picture types that are used in digital image processing: (i) binary images, (ii) gray-scale images, and (iii) color images.

IP requires machine learning (ML), which is employed in two ways: unsupervised for feature extraction and supervised for labeling objects for detection and recognition [33, 34]. Researchers openly publish many studies pertaining to the elicitation of important characteristics in a picture in unsupervised machine learning. Using the histogram and clustering method, segmentation is applied. Color-based segmentation in clustering is limited to Fuzzy C; comparable color pixels gather together to form clusters; in a similar vein, the K-mean technique is used to segment texture images [35]. Anticipation

In model-based segmentation, maximize the parameters of the algorithm by unsupervised operation [35].

Through the use of IP clustering, Zhong et al.'s work [36] successfully builds computational intelligence in optical remote sensing for a number of real-time IP applications operating on unsupervised ML approaches. Using a fuzzy clustering technique, Ghosh et al. build on unsupervised changes detection of remote sensing photos and compare two images of the same geographic region [37, 38]. Furthermore, it is extensively employed in the field of cardiovascular medical imaging, where it aids in the system's illness diagnosis; manually identifying malaria is a laborious operation that is prone to human mistake. Unsupervised automated identification of sensitive malaria screening methods was developed by Purwa et al. [39].

Unsupervised learning does not end here; instead, real-time applications encompass a wider range of topics. With supervised learning, computers are trained or tested on labeled datasets—labeled material that has already been marked for classification—in order to achieve learning objectives. Support Vector Machines (SVM) are extensively used in NLP for supervised learning in order to identify handwritten and scanned text images [40]. Sort cell biology into categories to identify medical imaging phenotypes [41]. In the field of robotics, supervised machine learning is essential to mobile robots' ability to visually perceive forest trails [42].

The terms "benign" and "malignant" are used by Erickson et al. [43] to identify brain tumors in medical images. The focus of Tuia et al. is on supervised learning in the categorization of remote sensing images [44].

3. Models of Neural Networks (NN)

Although deep learning (DL) is the newest concept in research, it is actually a branch of machine learning (ML); DL is simply the model name for neural networks [45, 104]. The concept of an individual's biological neurons gives rise to the idea of NN. Walter Pitts and McCulloch derived

the concept of perception in neural networks (NN) was introduced by Frank Rosenblatt, and a probabilistic model for information storage was financed by the US Navy and successfully implemented at Cornell Aeronautical Research Lab in 1958 [47]. Human neurons were first converted into artificial neurons in 1943 [46]. Weight is the main method of long-term information storage in neurons. If the weight is changed, the information storage of NN is also updated. Weight is the fundamental building block of neural networks (NNs), which are computational models that operate in parallel without the need for a central control unit. Three primary components comprise the architecture of neural networks (NNs): (I) neuronal number, (II) number of layers, and (III) connections between layers [48].

In feedforward neural networks (FFNNs), input values flow from input nodes to hidden neurons and back again. This is an acyclic network. Both single and multilayer perceptron's are used in feedforward; a single output layer is usually the basis for a single layer feedforward perceptron, or linear threshold [49]. The artificial neurons' activation function only fires when the threshold value is zero (0), and it comprises an aggregation of input values with weights. In order to stabilize the output, add the bias parameter if the threshold value is less than zero (-1); else, the model will become deactivated. When determining the threshold value of the activation function, bias is the constant intercept added to the product of aggregate input and weight (output = sum (input * weight) + bias) [1]. A multilayer feedforward perceptron (MFFP) has an input layer, one or more hidden layers, and a single output layer. Each layer's nodes are fully linked to the sublayers of the other layers to form a network [50]. Every layer is connected similarly to an acyclic network, but with a varying quantity of neurons. The primary goal of the backpropagation learning process is to lower the error rate by adjusting the NN weight [25].

When an error occurs during the feedforward phase of the model's operation, backpropagation returns to the previous iteration in order to maintain the probabilistic connection weight and minimize the error value. Gradient descent is the iterative process used in optimization techniques to minimize the loss function by changing the model's parameter, which is the neural nets' weight [51]. The magnitude of the steps we take to lower the rate of mistake in gradient descent is known as the learning rate. A high learning rate increases risk since it takes more steps to get the desired outcome. If we have a fewer steps are required to reach the objective with little risk, a low learning rate (local minima), and an efficient overall process [1]. The cost function (sometimes called a loss function) indicates the accuracy or performance of our model. In the graph, it creates its own curve and gradient. This sums up NN in its whole and concisely. Innovation in the artificial intelligence sector leads to development. In DL, NN stands for convolutional neural network (CNN)[52, 53]. CNN is an active learning algorithm [1], and the concept's primary goal is to create powerful AI that functions and thinks like a human [54].

The goal is to identify the visual characteristics of the input image, modify the weight and bias (if necessary), and distinguish one item from another [55]. Additionally, researchers used CNN primarily on a visual dataset in order to extract hidden information and train the system to detect various items automatically based on distinct aspects of a picture. In contrast to classification algorithms, CNN utilizes a low amount during the pre-processing stage and a high amount during the filtering process to provide sufficient training, or the capacity to learn additional characteristics. In this regard, classification algorithms are completely at odds with CNN. CNN's contribution extends beyond CV; the majority of its characteristics are employed in Natural Language Processing (NLP) to categorize sentences [56]. The interconnected patterns of brain neurons in the human visual cortex served as the model for CNN's design [57]. A single neuron only reacts in a small portion of the visual field at a time in the receptive field in architecture [58, 105]. Determining the fundamental distinction between DL and neural nets in this context, a NN model with more than two hidden layers is most often referred to as DL, emphasizing the key features of gradient descent, learning rate, loss function, convolutional NN, and CNN architecture.

4. Instruments and Software

The eleven most well-liked machine learning tools are included in Table 1 of this review article along with their characteristics, platform compatibility, commercial and non-commercial product offerings, and availability of related programming language domains.

Table 1: Machine Learning Tools and Applications

Tool Name	Support for Platforms	Paid or Unpaid	Language	Features
Scikit Learn [59, 60]	Windows Linux Mac OS	Non-paid	C C++ Python	Regression Classification Clustering Selection of Pre-processing Models
TensorFlow [61, 62]	Windows Linux Mac OS	Non-paid	Python CUDA C++	Dataflow programming library
PyTorch [63, 64]	Windows Linux Mac OS	Non-paid	Python CUDA C++	Module Auto grading Optimization Module
KNIME [65]	Windows	Non-paid	JAVA	Using plugins for text mining and image mining

	Linux Mac OS			
Weka [66, 67, 68]	Windows Linux Mac OS	Non-paid	JAVA	Data preparation, visualization, clustering, classification, regression, and association
Keras.io [69, 70]	Cross Platform	Non-paid	Python	Artificial Neural Network API
Rapid Miner [71]	Cross Platform	paid	JAVA	Preparing Data, Data Importing, Conversion, and Display
Shogun [72]	Windows Linux Mac OS	Non-paid	C++	Regression Support Vector Machine Online Learning Dimensionality-Reduction Classification Clustering
Accors.Net [73]	Cross Platform	Non-paid	C#	Test of Hypothesis and Kernel Techniques Signals, Vision, Audio, and Image Regression Clustering and Distribution Classification

Like the ML tools mentioned above, other apps address various fields of artificial intelligence (AI):
- The monitoring software in CV is called video surveillance. Considering that one person may watch several cameras at once, it becomes impractical to watch them all the time. It's all about CV, but at the backend, an ML train machine ad takes care of every scenario. Track anomalous criminal activity and warn security forces before it occurs.
- Everybody in the modern day uses the biometric system in an organization to take daily attendance. While each individual has a unique fingerprint, machine learning (ML) makes it feasible for the computer to recognize a person's identity when they punch in using biometrics.
- Pinterest is a resume software that recognizes items in photos and makes appropriate suggestions for related pins.
- Together, machine learning and collaborative image processing can quickly identify elements in a photo and make predictions about a person's appearance ten years from now. Likewise, use an old photo to infer a person's appearance based on elements from a more recent photo. The military uses this program mostly for investigative purposes.
- Beyond CV, the most notable example that is now popular is Netflix, which suggests movies based on pre-watching and has an ML-powered recommendation engine. Individuals you might know on Facebook are constantly observing things like profile visits, recent connections, page likes, ad clicking, employment, education, and so on. Facebook, which is always learning, recommends friends, pages, and advertisements that you should definitely connect with. Additionally, we may apply ML unsupervised learning to enable facial recognition on Facebook when we submit pictures of people.
- Spamming via email is restricted by a rule-based spam filter. The machine learning-powered system security tools that identify malware code patterns.
- The Google search engine uses machine learning (ML) approaches to manage user-clicked top results. Various backend algorithms manage results based on visits. Google uses machine learning (ML) for both translation and Gmail spam screening.

5. Massive Data Sets Needed for Algorithms to Perform Better:

In this situation, a machine cannot function as well as it should without a substantial amount of data for training. When the algorithm fails to match the data, bias increases and variance decreases, a phenomenon known as underfitting occurs. Overfitting is a different situation that can arise during training stages. It is characterized by model overload due to the ratio of training data, which can reduce bias and increase variance. Another crucial problem is the acquisition of reliable data that is helpful for subsequent processes. This is achieved by ensuring that data is in a certain domain while also collecting data from various sources.

6. Demand Detailed Labeling of Training Data Offline:

Currently, AI struggles with data labeling; about 80% of real-world data must be collected, organized, and labeled. Data labeling is a labor-intensive process that involves training, validating, and fine-tuning models. the enormous discrepancy between data recognition and data increase. Justification for extensive offline labeling: low quality, quantity, expensive or inefficient, and quality control. Calculate the estimated number of steps needed to transform unlabeled training data into labelled training data: (i) data identification; (ii) data aggregation; (iii) data cleaning; (iv) data augmentation; and (v) data labeling. Then, prepare the algorithm for the next phase. The steps involved in machine learning include (vi) optimization, (vii) tuning, (viii) training, and (ix) developing algorithms. These are the primary steps in the data labeling process that carry out the ML algorithm.

7. High Capacity Processing:

This is another difficult challenge for the field researchers to do. ML demands higher processing power to handle the dataset of input images. High processing takes longer to evaluate the vast volume of data and detect errors; it requires a cycle to determine whether the code is operating flawlessly. The total scenario is, in short, a time-consuming operation requiring a lot of computing power to calculate several records.

8. The ML model and algorithm don't work together:

Algorithms may be divided into two categories: similarities and learning styles. There are three types of learning style algorithms: supervised, unsupervised, and semi-supervised learning aspects. Instance-based, regression, regularization, clustering, decision-tree, and Bayesian algorithms are the primary examples of how similarity is used to group similar data together. The hybrid system becomes limited when it aims to work together with two algorithms to make use of both functions and increase the machine's power over other run-time systems.

9. Unrestricted Research Domains: Even though machine learning has been used extensively in computer vision research, there are still problems in the field.

Vehicle/Object Detection: In order to react rapidly to necessary objects or vehicles in conflict circumstances, effective algorithms for vehicle and object recognition are still needed, necessitating continued research in fast processing to detect, react, and avoid harm. Large-scale and compressed pictures are the dataset's challenges for effectively detecting things; this will make it easier to identify vehicles and keep track of their activities. The use of Maximally Stable Extremal Regions for vehicle detection in complex situations under low light conditions or under shadow regions will be aided by the development of advanced machine learning algorithms and models. However, poor visual quality and low resolution of the satellite image remain a problem in object/vehicle detection.

Recognizing Activities: Activity detection in photos and videos is still necessary. Effective ML-based models and algorithms that quantify indexing, rate, accuracy, robustness, efficiency, and identification of both single and many types and levels of activities.

Human posture approximation: This is a significant field of computer vision research as well, with its foundation in the examination of human posture in images. This is the method used to determine a person's true joint location in a picture or video. The localization of human joints in photographs remains a challenge for computer vision research. It's also critical to remember that pose estimation is divided into a number of smaller tasks, including single pose estimation, estimating poses in a crowd, estimating poses in images, and estimating poses in movies.

8. Final Thoughts:

This study addresses the processes of digital images and how challenging it is to feed the computer system, emphasizing the significance of machine learning (ML) in the image processing (IP) sector. The acquisition phase of this process is where the image loads and becomes ready for the next stage of IP (more on this in the section on image processing). Ultimately, we obtain labeled picture objects throughout the identification and acknowledgment stages. One of the machine learning (ML) methods, neural networks (NN), uses input values to optimize solutions to a given issue in order to produce a better solution and predict output. NN is used by many well-known companies to maintain their entire application portfolio. For example, Amazon, a globally recognized company, uses NN for its powerful recommendation engine; Microsoft uses NN for translation; Facebook uses NN for facial recognition and detection; Google uses NN for its Gmail spam filter, and so on. We've also spoken about the idea of deep learning, the burgeoning area of artificial intelligence (AI), which is a branch of machine learning (ML), and how the introduction of this technology is drawing interest from academics these days. We find that while machine learning has permeated every aspect of computer vision and is highly effective in every one of those fields, there are still certain unfilled research gaps that require attention from academics. These gaps are listed in the section on open research topics.

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