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Shallow Model and Deep Learning Model for Features Extraction of Images

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ABSTRACT

Applications trend today on artificial intelligence (AI). The latest development in the field of machine learning (ML) comes from deep learning which is expected to cause a powerful improvement in the field of artificial intelligence. Features Extraction(FE) is very important. These properties make it possible to characterize the issue and create models that explain a system or process. A variety of image preparation techniques or data sets, Different approaches are done to obtain a feature that will be used for artificial intelligence (AI) algorithms that projects involving ML or the trendiest and most well-liked fields, including deep learning. Algorithm selection techniques are vital in academic machine-learning research. This article discusses different categorization algorithms and new efforts to increase classification accuracy.

1. Introduction

In reality, information gathers a lot of data. It requires a process to comprehend this data. They cannot be processed manually. This is where the idea of feature extraction enters the image. Artificial intelligence-based systems typically combine human intellect with a one-time programming automation method to make decisions under critical circumstances [1]

Various techniques for handling sorts of data in Predictive data mining are the most significant of several ML applications. The same collection of features is utilized to represent every instance in every dataset that ML algorithms employ. The characteristics could be continuous or categorical [2][3].

FE is a quantity of information that gathers a lot of data. It requires a process to comprehend this data. They cannot be processed manually. This is where the idea of feature extraction enters the image.

These days, machine learning is one of the artificial intelligence's most well-liked sub-domains, making it the most popular study field. Making the system work is the foundation of its using historical data, an intelligent system. Machine learning techniques are used in many different contexts, including pattern recognition, image classification, model prediction, data mining, search engines, sentiment analysis, time series forecasting, structural health monitoring, and virtual personal assistants like Siri, Alexa, and Google Now. The primary objective of this work is to provide a summary of several ML techniques [1][2].

FE is a quantity of the dimensionality reduction preparation, considered an original set of the raw data separated and summary for further convenient gathering. FE is a unique type of reduction in dimensions processing. FE explains the pertinent shape information included in a pattern,

making it simple for a formal classification system to categorize the pattern[4]. The need for quick and efficient identification technologies is expanding in tandem with society's ongoing progress [5]. Traditional identifying technology has been replaced by biometric technology, which has rapidly advanced in variety, dependability, and simplicity [6].

Gender is a feature of looks that is largely constant [7]. Gender can be easily determined by humans, as shown in figure 1.

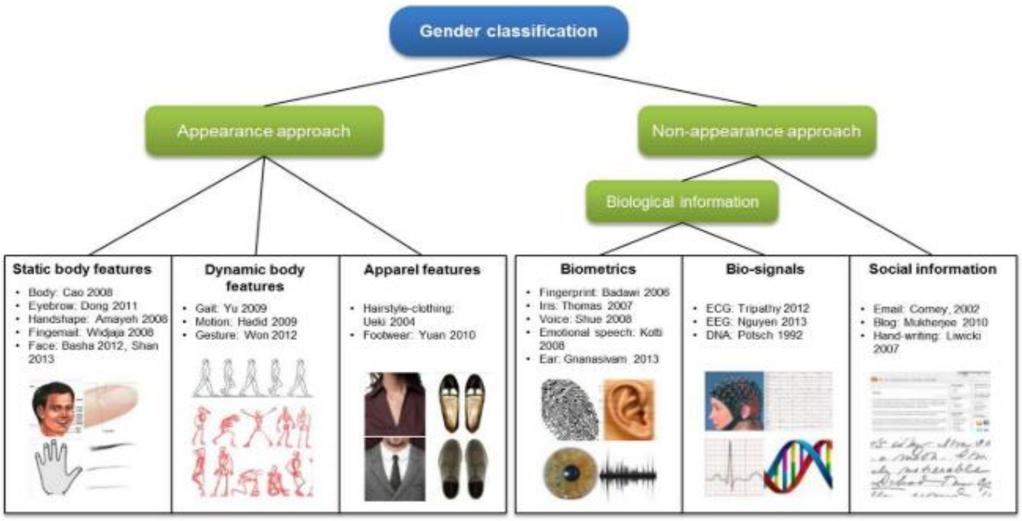

Figure 1:The human gender classification [7]

for the majority of faces, and additional data from hairdo, body type, attire, and brows, Framework for Classification. As shown in Figure 2, the gender classification framework typically consists of five steps: sensing, preprocessing, feature extraction, classification, and assessment.

In 2017 Shanthi, C. and Pappa, N. presented six different flow pattern movies that are recorded over time and then transformed into 2D images for processing. The textural and form data are acquired by image processing [8].

In 2021 Qing Kuang presented a training classification approach using a deep learning model demonstration feature extraction algorithm. The data set that has been preprocessed by the filter in this paper is fed into the network using the local quantization method. The CNN network is taught to produce high-resolution features and has been given a depth of four layers. The findings demonstrate that deep learning has a greater capacity for automatic feature extraction than shallow learning. The deep learning model is strengthened by the rich environment design function, which also aids in the development of more distinctive features. This feature extraction technique has a transparent hierarchy.

2. Feature Extraction

When extracting features, a human expert might opt to apply or ignore certain processing methods. There is limited prior knowledge regarding categorization models' effectiveness, based only on details of the assignment [9].

In general, feature selection algorithms consist of two parts: a measuring tool that evaluates how "excellent" an idea is for a feature set, and a selection algorithm that generates suggested feature subsets and seeks out an optimal subset. However, iterate through the space of subsets without a suitable stopping criterion, wasting significant computational effort. Two possible stopping factors are if adding (or removing) a characteristic does not result in a superior subgroup, and whether the subgroup reached is optimal in terms of some evaluation function[10].

Models for supervised machine learning that are accurate. They are frequently unreasonably influenced by that a lot of features depend on each other. Utilizing the core feature set as a foundation, you can develop new functionalities. The development of clearer and more precise classifiers could be facilitated by these recently developed features. The identification of significant traits also improves the readability of the created classifier and the comprehension of the learned concepts[9]

3. Algorithms Selection

One of the most important decisions is the learning algorithm to choose. Most frequently, prediction accuracy is used to evaluate the classifier as the proportion of accurate predictions. At least three different techniques are used to assess the accuracy of a classifier. Using two-thirds of the training set for training and the remaining third for performance estimation is one method. In a different method called cross-validation, the training set is split into equal-sized, mutually exclusive subgroups, and the classifier is trained on the union of each subset.

The classifier's error rate is consequently estimated by averaging the error rates of each subset. Cross-validation is a specific example of leave-one-out validation. One instance is present in each test subset. Although the cost of using this approach of validation is higher, it is advantageous when the most precise estimation of the error rate of a classifier is needed. Investigating the following problems is necessary if the error amount evaluation is unacceptable. Comparing supervised machine learning algorithms statistically is a frequent way to do this as shown in figure 2 and figure 3 [11][12][13].

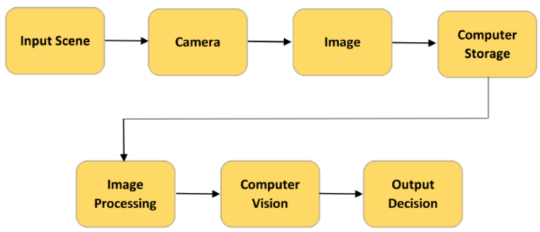

Figure 2. The basic architecture of the computer vision system

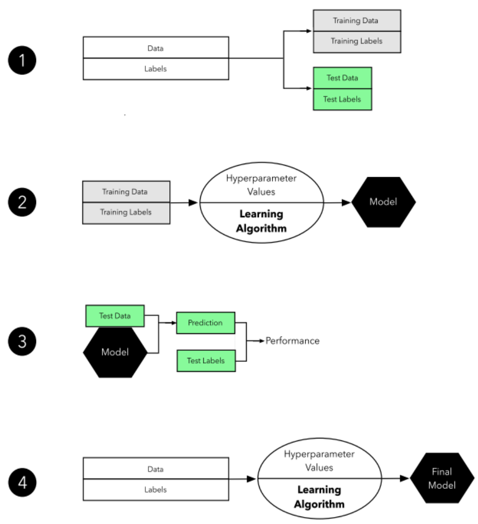

Figure 3. Visual summary of the validation process

4. Machine Learning for Classification

Supervised ML algorithms problem gathering the dataset is the initial stage. If the necessary expertise is on hand, may advise on the fields. However, a dataset gathered using the "brute-force" approach

isn't necessarily appropriate for induction. It typically has noise and missing feature data, therefore extensive pre-processing is necessary.
A more modern method, classification, enables the machine to extract information without human input. Here, the machine learning field's so-called "deep learning" branch[14]. There are numerous classification methods [15]. Even after looking at the facts, there are times when people are unable to assess or extrapolate the knowledge. Then, researchers apply ML in that circumstance. How to make robots learn without being explicitly programmed has been the topic of numerous studies. This problem, which includes a significant amount of data, is solved by many mathematicians and programmers using a number of methods. Even after viewing the data, show figure 4 [3] [16].

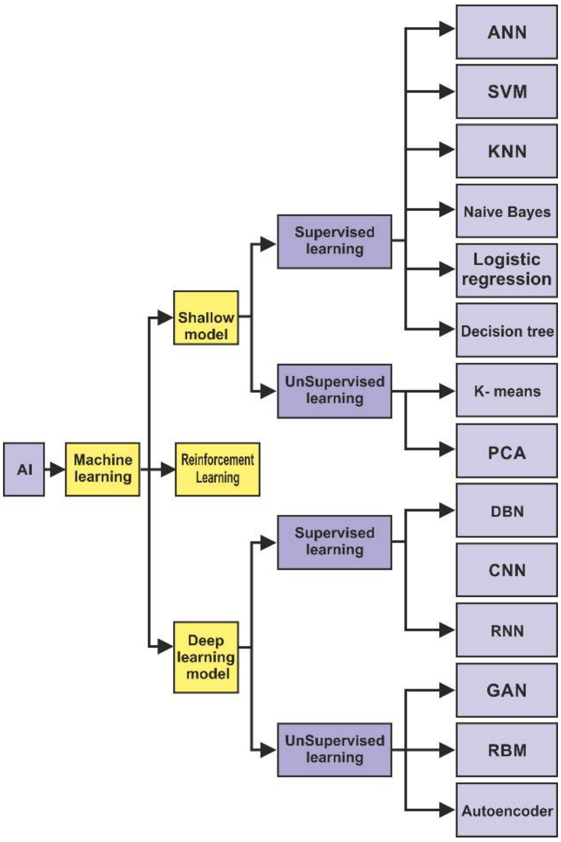

Figure 4. Classification of machine learning methods

4.1 Supervised learning algorithms

These are referred to as unsupervised learning because there are no proper answers and no teachers, in contrast to the supervised learning discussed above. It is up to the algorithms to manage on their own[16] [17].
to identify and present the data's intriguing structure. The unsupervised learning algorithms only extract a small subset of the data's features show figure 5. [18].

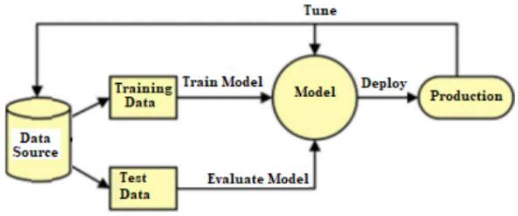

Figure 5.Supervised learning

4.1.1 Neural Network

The behavior of an artificial neural network is identical to that of the human brain. the functions on three layers. Data are sent to the input layer. The buried layer handles input processing. The output layer then transmits the chosen output, shown in figure 6.

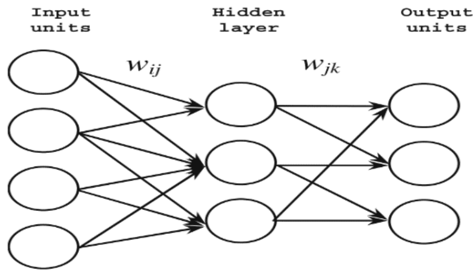

Figure 6. Neural Networks

The output of an input in a supervised neural network is already known. If The expected and actual outputs of the neural network are compared. The parameters are modified in response to the error, and the neural network is then fed once more. As seen in figure 7, the feed-forward neural network uses a supervised neural network.

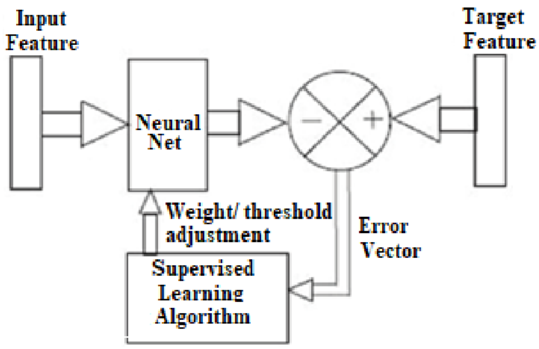

Figure 7. Supervised Neural Network

4.1.2 Decision Tree

A decision tree is a graph that displays options and their outcomes as a tree. The edges of the graph serve as the conditions or rules for making decisions, whereas the nodes in the graph represent an event or a choice. There are nodes and branches in every tree. Each node represents a collection of characteristics that need to be categorized, and each branch indicates a potential value for the node[10].

4.1.3 Naive Bayes

A Naive Bayes classifier, to put it simply, believes that the presence of one feature in a class does not influence the presence of any more characteristics. The Nave Bayes algorithm is often used for text classification. Considering the potential chance of occurrence. It is mostly used for classification and grouping purposes. In addition to recommending a specific point [19].

4.1.4 Logistic Regression

Regression analysis is focused on fitting a curve using training data to determine the best course of action for situations involving continuous values. It creates a mutual link between the parameters based on the mistake that the trained model predicts. When there is a need to make a continuous forecast, regression methods are applied. Regression analysis is focused on fitting a curve using training data to determine the best course of action for situations involving continuous values. It creates a mutual link between the parameters based on the mistake that the trained model predicts. When a forecast needs to be produced and the solution space is huge or infinite, regression methods are used. Popular regression algorithms include[1].

4.1.5 Support Vector Machine

Another well-liked method of contemporary Support vector machines (SVM) is used in ML. SVM uses supervised learning models and related learning techniques, SVM analyzes data from regression and classification studies. SVMs may effectively carry out both linear and non-linear classification by implicitly translating their inputs into high-dimensional feature spaces. The margin and the classes to reduce the classification error, show in figure 8 [20].

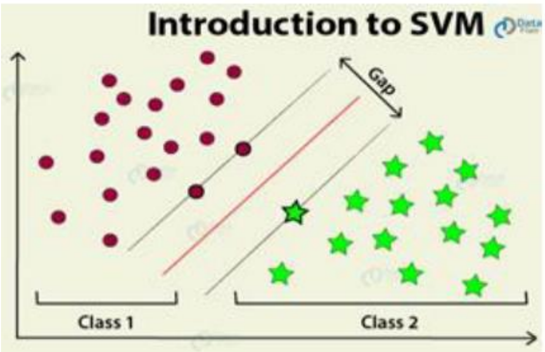

Figure 8. Support Vector Machine

4.1.6 K-Nearest Neighbor

Supervised machine learning techniques like K-nearest neighbors (KNN) can be used to resolve classification and regression issues. Despite being simple to use and comprehend, it has the serious drawback of becoming significantly slower as data usage increases as shown the code in below.

```
k-Nearest Neighbor
Classify (X, Y, x) // X: training data, Y: class labels of X, x: unknown sample
for i = 1 to m do
  Compute distance d(X_i, x)
end for
Compute set I containing indices for the k smallest distances d(X_i, x).
return majority label for {Y_i where i ∈ I}
```

KNN code

4.2 Unsupervised Neural Network

The neural network does not know either the input or the output. The network's main task is to group the data according to some commonalities. Based on how closely the inputs relate to one another, the neural network organizes the data, shown in figure 9.

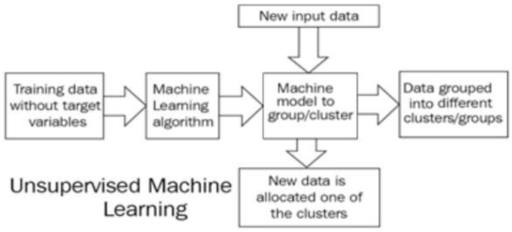

Figure 9.Unsupervised Neural Network

4.3 Unsupervised Learning:

The unsupervised learning algorithms only extract data from a limited amount of characteristics. When new data is introduced, it employs the features it has already learned to determine the data class. Feature grouping and reduction are its primary uses[3].

4.3.1 Principal Component Analysis

Principal Components Analysis (PCA) In the statistical procedure known as principal component analysis PCA. An orthogonal transformation produces a set of values for a set of linearly uncorrelated variables known as principal components from a set of observations of potentially correlated variables. To speed up and simplify computations, this decreases the dimension of the data. It is applied to explain the variance-covariance structure of a collection of variables using linear combinations. It is commonly used as a technique for dimensionality reduction, as seen in figure 10 [21][22].

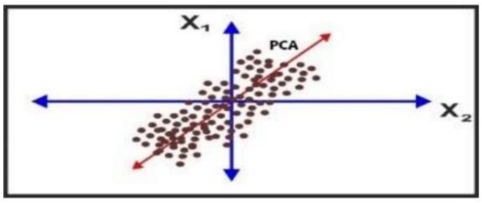

Figure 10 . PCA Technique

4.3.2 K-Means Clustering

K-means is one of the simplest unsupervised learning methods for dealing with the well-known clustering problem. A preset number of clusters are used in the procedure to clearly and simply classify a given data set. The main concept is to define k-means, one for each cluster. Because different places have varied effects, these centers need to be strategically positioned. Therefore, it would be prudent to position them as far away as feasible show figure 11[3].

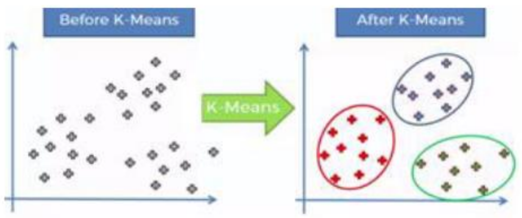

Figure 11. K-Means Clustering

4.4 Reinforcement Learning

Reinforcement learning is a branch of machine learning that examines. Along with supervised learning and unsupervised learning, when optimal policy through trial and error to solve sequential decision-making, is shown in figure 12 [23].

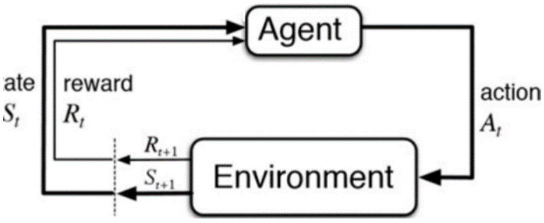

Figure 12. Reinforcement Learning

4.4.1 Reinforced Neural Network

Network neural Reinforcement learning is the study of goal-oriented algorithms that learn to maximize along a particular axis across several iterations, such as increasing the total amount of points scored during a game. They can start from scratch and, under the right conditions, they have superhuman abilities. Similar to a kid who is encouraged by spanking and sugar, these algorithms are penalized for bad assessments and rewarded for good ones. it's called Reinforcement learning; see figure 13 [24].

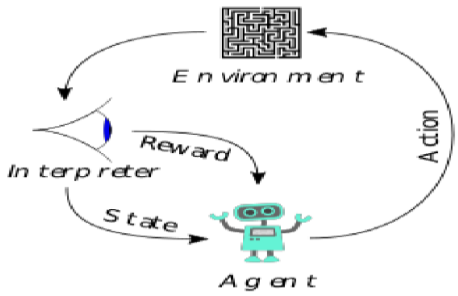

Figure 13. Reinforced Neural Network

4.5 Deep Learning

4.5.1 Supervised Deep Learning

The objective of discriminative deep architectures and supervised learning is to be able to recognize [25].

4.5.1.1 DBN Model Deep

Deep Belief Network (DBN) DBN is often appropriate for modeling one-dimensional data. A probability-generating model that is a part of the unsupervised learning method is called the (DBN). There are several Restricted Boltzmann Machines in it (RBM). RBM is a useful technique for extracting features, allowing DBM to extract more abstract features by stacking additional RBM. The figure represents an example of a DBN structure, shown in figure 14 [26].

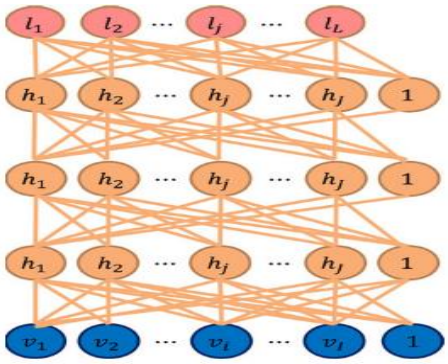

Figure14. The structure of DBN

4.5.1.2 Convolutional Neural Network (CNN)

Convolutional neural networks (CNNs) have been employed for visual tasks since the late 1980s. They advanced and were at the vanguard of a neural network renaissance that has experienced fast development since 2012 thanks to the advent of massive volumes of labeled data and the addition of stronger algorithms. The use of CNNs to solve images classification problems is the main topic [27][28] show in figure 15

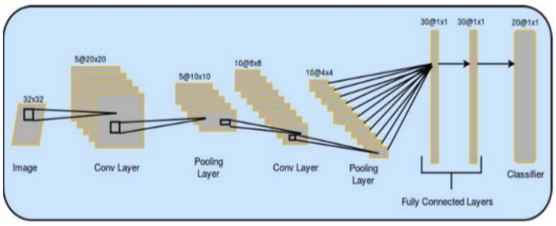

Figure15. Structure of CNN

4.5.1.3 RNN Deep Learning

In deep learning RNNs, the sharing states are divided into a few layers to take advantage of the positive aspects of "deep" architectures. Building RNNs with "deep" designs is considered to offer a significant benefit, figure 16 presents the functional network and its developing topological graph to demonstrate the operation of a deep RNN with N layers [29].

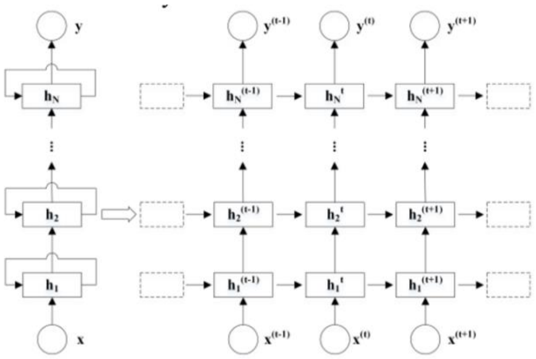

Figure 16. The computational layer deep-RNN

4.5.2 Unsupervised Deep Learning

Unsupervised learning, also known as generative architectures, uses unlabeled data. Unsupervised learning or pre-training is the basic idea behind using generative architectures for pattern recognition[25].

4.5.2.1 GAN Deep Learning

One deep learning model called Generative Adversarial Networks (GAN) was developed using zero-sum game theory and is now a popular area of study. By utilizing unsupervised learning to acquire the data distribution, the model variation aims to deliver more precise and realistic data. Due to their vast potential for use in areas like video and language processing computers for images and vision, etc. Currently, GANs are the focus of a lot of studies. The history of the GAN, its theoretical models, and its extensional versions are presented in this study. The versions can further enhance the original GAN or change its core structures as shown figure17 [30].

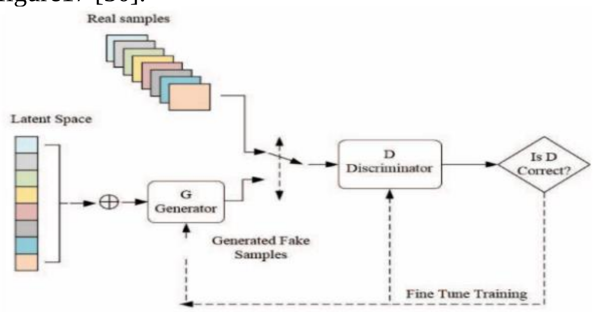

Figure 17. The Structure of GAN

4.4.2.2 RBM Deep Learning

A restricted Boltzmann machine (RBM) is an undirected, bipartite graph with two layers: one that is visible and the other that is concealed. By treating each pair of consecutive layers as an RBM, the stacked RBM is known as the deep belief network (DBN)[31].

4.4.2.3 Autoencoder Deep Learning

The idea of autoencoding has inspired a variety of (unsupervised) representation learning algorithms, To roughly recover the original observations from the lower-dimensional representation, each of these seeks to learn a mapping from high-dimensional observations to a lower-dimensional representation space. It contends that despite the diverse goals and design decisions of different approaches, almost all of the techniques examined in this study either implicitly or explicitly[25][26][32].

5. Conclusion

If the extracted features are appropriately selected, Instead of using the full-size input. The intended goal will hopefully be accomplished by the features set by extracting the information needed from the incoming data. Recognition and categorization of images is a growing area of image processing.
Both supervised and unsupervised ML exist. Select supervised learning if you have fewer data points and well-labeled training data. For huge data sets, unsupervised learning typically performs and produces superior outcomes. also, use deep learning methods if you have a sizable data collection that is easily available. Deep reinforcement learning and reinforcement learning were also researched. have improved their knowledge of neural network applications. Several different machine learning algorithms are surveyed in this paper. Whether consciously or unintentionally, everyone uses machine learning from updated photographs today.

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