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Assessing Effectiveness of Exercised Variants of Machine Learning Techniques

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Abstract**:** ***Currently, the research field of machine learning is receiving more attention due to the automatic visual inspection of different tasks. Thus, the machine learning scheme is incorporated with deep learning and artificial intelligence technology. However, there are different schemes (perception based, instance-based and logic based) to provide an effective classification, prediction, and data recognition in terms of characterizing the features at different conditions to design a suitable module. This investigational study provides a comprehensive study on different algorithmic approaches which are categorized in terms of classification-based, prediction-based and segmentation based approaches. Also, this study evaluates the performance of various machine learning methods and their applications in different fields and also their limitations. Finally, this study leads to identifying the research gaps in the machine learning approach, which can be addressed by further research.***

Keywords **:** ***Machine Learning, Artificial Intelligence, Deep Learning, Classification, Recognition, Prediction.***

I. INTRODUCTION

In current times machine learning (ML) is one of the more sounding and fastest growing technologies in various fields for different kind of tasks. Especially, ML is the major success factor in the ongoing digital transformation across industries. Previously, humans only could do the task with experience but presently ML technology is the better method to learn the task and perform those tasks better, faster, and more intelligently [1]. The definition of Machine Learning according to Tom M Mitchell is "A human or computer program is said to learn from experience 'E' based on some task 'T' and the task performance is measured by P, if the performance 'P' of the task 'T' is improved by experience 'E' then it is said the machine is learning" [2]. Based on this definition the block diagram of ML is as shown in Figure1. The name machine learning is invented in 1959 (by Arthur Samuel); pragmatically it has been started since the 1970s when the algorithm has taken place which is related to improve it, and recent days these tools are more widely grooming and making more noise to reach the requirements of the users [1]. It was mainly developed by the study of pattern recognition, classification and prediction to manipulate the application having a problem of non-linearity.

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Mainly a machine learning method includes four steps such as prediction, classification, and regression with performance evaluation. Initially choose the basis like attributes and features for the prediction using feature engineering, next find and select the appropriate algorithms such as classification and regression for complexity minimization and faster processing. Later, train and evaluate the performance of the model. Finally, classify and predict the unknown data using a trained model [1]. The machine learning task is mainly classified into two, which are i) Supervised Learning (SL) ii) Unsupervised Learning (UL). The supervised learning is the task which involves allocating labeled data so that a certain pattern or function can be deduced from that data. Primarily, in SL the data input is known which is appropriately labeled and the major task developed is classification and regression. Unsupervised learning is the process to determine the hidden patterns or grouping data from the unlabeled data. In this task, the system does not know the input and output information, and it is mainly developed to do clustering and association. ML leads to many applications in industry 4.0 era such as banking and financial sectors, retail, healthcare, vehicles (self-driving car) etc. However, it exhibits many advantages as well as disadvantages and limitations. Some of the advantages are: It is used to handle multi-variant and multidimensional data (nonlinearity) in dynamic environments, it permits time cycle reduction and efficient utilization of resources, it can handle complex and large process environment by using some of the relevant tools, it can lead to independent tasks like handling of autonomous computers or software programs. Apart from this ML has some of the limitations such as - Getting relevant data is the major challenge i.e., data needs to be processed before providing it to relevant algorithm as an input, lack of variability in different situation and conditions, the output result understanding is the big challenge to obtain effectiveness of ML algorithms, error diagnosis and correction, time constraints in learning, verification problems, and limitations of predictions.

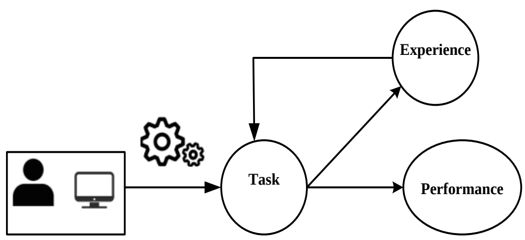

Fig.1 Block diagram of Machine learning [2]

Various researches adopted the different forms of machine learning approaches to overcome the limitation and also to meet the user requirements. Such methods are decision tree learning [3] [4], artificial neural networks (ANN) [5], deep learning [6] [7], associate rule learning, inductive logic programming [8], support vector machine [9][10], clustering [11], reinforcement learning[12][13], bayesian network [14], similarity and metric learning, genetic algorithm and rule-based machine learning. Most of the researches have not reached the benchmark that has been observed by the study of literature with various kinds of limitations. This survey paper briefly explains different research techniques and future research direction of ML to obtain user- usefulness and user -possibility.

The structure of this survey study can be organized as: section II illustrates the related work in machine learning and section III presents the machine learning types along with more popularly used techniques. Section IV explains the algorithms commonly used in machine learning process. Further, the evaluation of machine learning using mathematical model is expressed in section V. The trends of ML tool and Matlab programming language and applications are illustrated in section VI and VII. The machine learning research trends are dealt in section VIII followed by the research gap in section IX. Finally the study is concluded in section X.

II. RELATED WORK

This section discusses the prior research study on supervised and unsupervised learning to improve the performance of machine learning.

The supervised learning schemes are expressed in many of the research studies as illustrated below:

Wu et al. [15] have presented supervised learning (Weakly and Semi-supervised) for multi-label image annotation. There are three types of algorithms weakly supervised; semi-supervised and weakly semi-supervised which have been adapted for image labeling and image annotation. The method was evaluated by considering convolutional neural networks and benchmark datasets for multi-label image description. The performance of the presented method is calculated by comparing the outcome with other existing methods like softmax, pairwise ranking, WARP, W^2PR, WeSed. The extensive comparative analysis shows that the presented technique (WeSed) excels better outcome with respect to both labeled and unlabeled image annotation.

- **Scope of applicability of [15]: Image Annotation**

Li et al. [16] have proposed an efficient design exploration (DSE) method for semi-supervised ensemble learning (SSEL) using Latin cube sampling technique. The method is evaluated based on SSEL by considering some benchmarks and hence the present method shows enhanced performance by reducing time, cost and accuracy enhancement. The prediction accuracy was tabulated in terms of RMAE (Root Mean Absolute Error), MSE by comparing the previous related method based on ANN and SVM.

Mera and Branch [17] have discussed the various techniques and algorithms for class imbalance learning problems on automatic visual inspection. The traditional machine learning which is trained with imbalance set of data that influenced towards only majority classes; hence it will produce poor performance towards minority class. Thus, this method has given better directions to the researchers for a further research study on this context.

- **Scope of applicability of [17]: Automatic visual inspection**

Liu et al. [18] have introduced an ensemble learning method - a random forest construction (RFC) with small size dataset for classification in a different kind of application in machine learning. The problem of semi-supervised node splitting (SSNS) is addressed and solved by adopting three criteria or methods such as SSNS with a kernel based density approximation, AMISE (Asymptotic Mean Integrated Square Error) based Bandwidth selection and density estimation on low dimensional subspace. The experimental results of the proposed method provide more efficient results which highlight many applications: data classification, object and scene categorization, face recognition, image segmentation, etc. The performance of this experimental study was calculated by comparing the present method with other existing methods.

- **Scope of applicability of [18]: Computer vision application**

Reynen and Audet [19] have presented a supervised machine learning (SML) on a network scale which utilizes event classification and detection at different network sizes and settings. The methodology adopted for feature classification which describes the feature selection and creation, and many machine learning applications.

Similarly, the event detection is considered as the extension of event classification where the addition of the reversed class, time series probability calculation, and association algorithm are utilized. The present method is efficiently detected and classifies the events (like blast and earthquake) using chosen data sets. It also finds the station and network accuracy, and detection summary in Oklahoma, and US state.

- **Scope of applicability of [19]: Detection of seismic event detection and classification**

Champigotto et al. [20] have proposed an active learning Pareto (ALP) front which recovers a different kind of multi-objective optimization problem. The ALP algorithms with various approaches and framework of the model have been briefly discussed.

It also discusses the process of learning for a regression task. The experimental result of ALP provides efficient and accurate Pareto front approximation with less computational complexity compared to other existing methods.

- **Scope of applicability of [20]: Application associated with uncertainty sampling principal**

Long et al. [21] have introduced a deep learning transferable representation with joint learning for enabling the scalable domain adaption.

The framework of scalable domain adaption network contains multi-kernel maximum mean discrepancy, transfer de-noising auto encoder and transfer deep learning. This method utilized a linear time learning algorithm; it represented by considering the kernel network parameter, learning the kernel parameter and generalizing error analysis.

In the experiment, the author has used some of the datasets or tasks like the multi-domain sentiment, email spam filtering, new group classification, visual object recognition and the evaluation results of these has been calculated. The proposed framework gives a high performance as compared with other related state-of-the-art methods.

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- **Scope of applicability of [21]: Text mining application**

Kemker and Kanan [22] have presented self-taught learning for image classification. This method is unsupervised learning, i.e., self-taught learning which allows learning the features from the unlabeled hyperspectral image (HSI). The model is trained with more number of unlabeled data sets which are differing from the target data sets. The framework of the method uses two learning approaches such as shallow approach which helps for independent component analysis, and the next one is stacked convolutional encoder in three layers. The present scheme is evaluated on several benchmark datasets (HSI), and it provides superior performance.

- **Scope of applicability of [22]: Image classification**

The work carried out by Nikhol [23] has introduced the autonomous robotic palpation using SML for segmenting hard inclusion in soft tissue. In the process, the system utilizes a Markov random model and EM (Expectation Maximization) algorithm for accurate classification. The outcome of the addressed method is segmented and classified results with high specificity and sensitivity.

- ***Scope of applicability of [23]: Biomedical system***

The satellite image classification using the convolution neural network is presented in Lunga et al. [24]. The author has considered the interactive learning mapping workflow based on various multiple modules to append a CNN model for better classification. There are many sub-modules presented – hashing modules are used to diminish the error or redundancy and noisy input samples from the randomly selected instances, and the ranking module is utilized to reduce the dominance of source from the marker field. The experimental results are conducted based on conditions or image characteristics such as multangular, multisensory, and it provides high precision performance compared to the other related model.

- **Scope of applicability of [24]: Image classification**

Similarly, the image classification or factorization is proposed in Gonen and Kaski [25] where the Kernel bases Bayesian Matrix are used for classification of data. The method introduces two scenarios- computing an Efficient Vibrational Approximation (EVA) system with the help of probabilistic model and Coupling Matrix Factorization (CMF) using multiple kernels learning to collect all the information from the multiple sides for integrating into the model. The performance of the exhibited method calculated and compared with the five other related works which shows a less hamming loss with efficient results.

- **Scope of applicability of [25]: Image in painting and bio-informatics application**

The unsupervised learning schemes are expressed in many of the research studies which are illustrated below.

Zitlau et al., [26], introduces a stacking that is one of the machine learning techniques for estimating the photometric redshift. The stacking method for finding the benefits are applied to the unsupervised and supervised learning based on self-organized maps (SOM) and decision trees methods. Also, by boosting the stacking algorithm by applying to an AdaBoost, this shows that the ratio of improvement shrinks with reducing computational cost.

- **Scope of applicability of [26]: Analysis of photometric and spectrometric data**

Graff et al. [27], presents a SKYNET which is neural network training tool used for machine learning astronomy. This network is more efficient and robust to train large feed forward neural network, auto encoder and to choose the number of hidden layers and nodes. It provides a wide range of application in supervised and unsupervised learning such as classification, clustering, dimensionality reduction, and regression, etc.

- **Scope of applicability of [27]: Astronomy**

Filippo et al. [28], presents a machine learning technique using resource management algorithms for multi-stage video streaming by the quality of experience. In video classification, machine learning utilizes the combination of both unsupervised and supervised approaches for automatic quality of extraction of the unknown video stream by using Boltzmann restriction machine and the linear classifier. The performance analysis of the resource management and video admission control algorithms provides a high quality of service to the end user.

- **Scope of applicability of [28]: Dynamic video streaming**

Giacoumidis et al. [29], introduces machine learning based unsupervised clustering for coherent multicarrier single or multi-channel signal (coherent optical OFDM) to tackle nonlinearities. The machine learning clustering (MLC) algorithm utilizes hierarchical clustering and Fuzzy logic C-mean clustering for coherent optical OFDM. The experimental results by taking the setup of OFDM equipped with clustering and the performance of this method is measured by comparing with all MLC algorithms, F-SVM, ANN, and IVSTF.

- **Scope of applicability of [29]: OFDM system**

Ge et al. [30], discusses the data mining and analytics applications in industries over the past decades. The methodology has the following steps: data preparation, data pre-processing, model selection, and training and performance evaluation. The machine learning (ML) is the key role of this process; the author has discussed eight unsupervised learning, ten supervised learning, and semi-supervised learning applications. Also, it provides the perspectives for future researches on this.

- **Scope of applicability of [30]: Process industry**

Abdelgayed et al. [31], presents a semi-supervised machine learning approach which handles mixed data (unlabeled and labeled data) for fault classification in both the transmission and distribution systems by considering the microgrids. In the process the system utilizes a discrete wavelet transform for extracting the hidden features of voltage and current waveform; harmony search algorithm also applied for finding the optimal wavelet parameter. Experimental results of the present method provide high performance in terms of flexibility, additivity, and accuracy.

- **Scope of applicability of [31]: Fault classification and object detection in distribution system**

The feature classification of data based on unsupervised learning is presented in Dao Lam [32] where the Radial Basis Function (RBF) and graphics processor are used to improve the speed and accuracy. The features are learned through the unsupervised learning model then that features are trained by RBF- Extreme learning model.The kernel based Customized Unified Device (CUD) architecture is established to enhance the speed of the RBF computation further. The results of the introduced method achieve high accuracy and speed of taken data set.

- **Scope of applicability of [32]: image classification and object detection**

The investigations of spectrum occupancy in cognitive radio using various machine learning methods are presented prior research study of Azmat and Chen [33]. Both supervised and unsupervised learning technique is used such as decision tree, SVM, Hidden Markov Model (HMM) to calculate the most substantial classification accuracy with the best scheme. Based on the experimental result the SVM classifier is one step forward among the all supervised and unsupervised classification.

- **Scope of applicability of [33]: Cognitive radio**

The research works of Zang et al. [34] have introduced the deep learning model for feature learning (unsupervised learning) of big data. The method used a tensor for computing the multifaceted correlation of heterogeneous data. The High Order Back Propagation Model (HBP) is used to train the parameter of the presented model. The performance of the presented method is calculated by comparing the present results with other methods such as an auto encoder and multimodal deep learning by considering four data sets.

- **Scope of applicability of [34]: Feature learning on heterogeneous data**

III. MACHINE LEARNING AND APPROACHES

The ML requires many techniques for a separate class of learning. An appropriate example of machine learning, the teacher teaches a subject to a student; the student will learn the subject day by day with some previous learning experience. If the student is learning and performance is enhanced then conclude that teacher's teaching method is efficient or call it as student is learning. Otherwise, a method of teaching has to be changed; such that student will learn fast with less period of time. Machine learning employs two types of learning methods such as Supervised and Unsupervised learning; Figure 2 shows the classification of ML with different techniques.

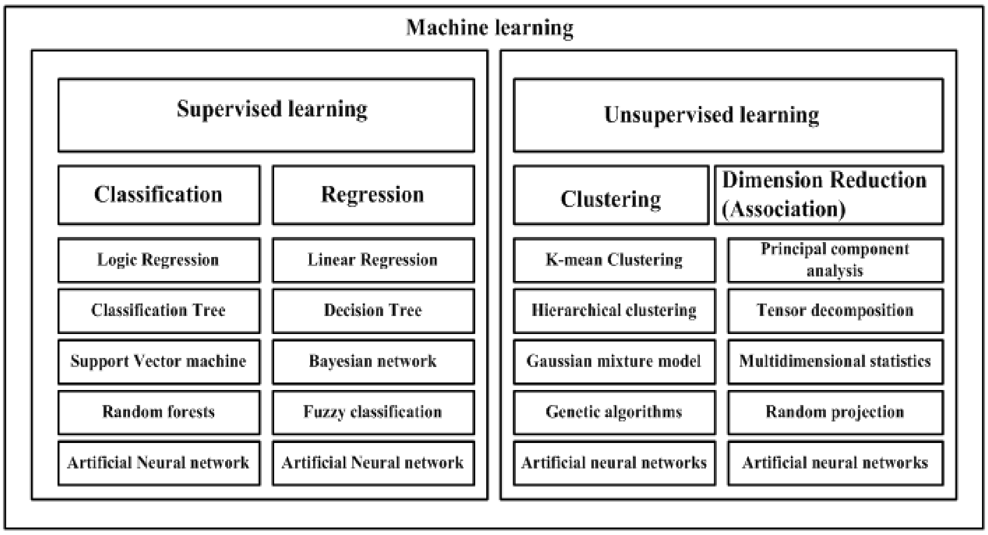

Fig.2 Machine Learning Approaches [1]

A. Supervised Learning (SL)

Supervised Learning in which input or training data has predetermined label (e.g.: positive/negative, true/false, spam/not spam) with the correct output of that data. This task is like, giving some task or problem to a student with their solutions and tell them to figure out or solve other similar kinds of problems. It contains classification and regression algorithm. Classification algorithms, which take as input dataset and take a class of each section of data, therefore, computer, can learn the task for classifying novel data. The classification employs logic regression, support vector machines, classification trees, artificial neural network (ANNs), random forests, and other related algorithms. Similarly, regression algorithms predict a value of an object's characteristics to perform process [35] [36]. This algorithm includes linear regression, fuzzy logic, decision trees, ANNs, Bayesian network [37].

B. Unsupervised Learning (UL)

Unsupervised learning in which training data or inputs are unlabeled, i.e., the training set have data, but it does not contain solutions; hence computer has to find the solution by own. In this, it's like a set of pattern giving to a student and tells them to calculate or figure out the underlying themes that produced the pattern. It contains clustering and association or dimensionality reduction algorithm [38]. Clustering algorithms that take input as a dataset covering with all different dimensions, then it partitions into cluster satisfying certain conditions. Some of the well-used algorithms in this method are a k-mean cluster that helps to partition the dataset hence each observation lies closest to the mean of its cluster [39]. There are some other clustering techniques, Gaussian mixture modeling, hierarchical clustering, genetic algorithms, and ANNs [40]. Next one is association or dimensionality reduction algorithm which takes the dataset that covers various kinds of dimensions then projects the data to fewer dimensions. These smaller dimensions are trying to capture the fundamental aspects of data.

This algorithm includes tensor reduction, random projection, multidimensional statistics, principal components analysis, and ANN.

IV. ALGORITHMS GROUPED BY SIMILARITY

This section, briefly explains the algorithms [41-47] which are utilized in the ML process.

A. Regression Algorithms

Regression analysis is the process of modeling the relationship between each variable, or it is a part of predictive analytics which exploits the co-relation between dependent and independent variables. Some of the mainly used regression models are: linear regression, logistic regression, multi-adaptive regression, stepwise regression, locally estimated scattered smoothing and so on.

B. Instance-based Algorithms

This algorithm is one kind of memory or instance-based learning model stores instance of training data instead of developing a precise description of the target function. It performs whenever new issues or problems arrive, and it is examined in accordance with saved memory or instances to find and predict the required goal function value. Also, it takes a new value and stores it whenever it feels that is better than the former. Hence this is known as 'Winner-take-all-method.' Example learning vector quantization, k-near neighbor, locally weighted learning, self-organized map, etc.

C. Regularization Algorithm

It is the process of counteracting over fitting, or it is used to abate the outliers. This algorithm acts as a powerful modification which is augmented with other existing machine learning models like a regressive model. Mainly, it used to smooth up the regression line by criticizing any bent of the curve which helping to try to match the outliers. There are some examples of ridge regression, least absolute shrinkage, and selection operator, least-angle regression, elastic net, etc.

D. Decision Tree Algorithms

Decision tree method is one of the most significant branches of inductive learning which is more widely used in different types of application of machine learning. It plays for extracting classification knowledge from the set of feature-based instances. According to the heuristic information, it will create a decision tree from the instance table, and by using a set of rules, it will classify some instances. In the construction of the decision tree, different methods have been adopted. For generating this, first, consider root node of the tree, and then split this into sub-node using some heuristic information. It will repeat until the existence of a leaf node.

E. Support Vector Machine (SVM)

Support vector machine is a supervised learning model with different associated algorithms, and it is one of the accurate and robust methods in machine learning for feature classification and regression of data. The support vector classification is based on boundaries; it separates the data into two groups from the set of instances based on the different feature. It supports both linear and nonlinear classifications and binary and multiclass classification. In the process of classification, the input vector first located into the hyperplane, based on the feature which falls one class of data into one side of the hyperplane and position of other class of data that fall into other side of the hyperplane. In case the data are not linearly separable then it goes to kernel functions to map them into higher dimensional spaces hence they separate accurately.

F. Bayesian Algorithms

It is one of the groups of machine learning algorithm that employs Bayes' theorem is used to solve the problems like classification and regression. There are some examples like Gaussian native Bayes, Bayesian Belief network, Multinomial native Bayes, etc.

G. Clustering Algorithms

Clustering is the method of placing similar data objects into clusters based on data similarities. This is one the more appropriate and frequently used unsupervised learning techniques. The algorithm can be characterized into seven groups like graph-based clustering algorithm, a hierarchical clustering algorithm, partitioning clustering algorithm, grid-based clustering, density-based clustering, combinational clustering, and model-based.

H. Deep Learning Algorithms

This is the more modernized version of ANN's which is used to a plentiful supply of data today. It is a part of machine learning that helps to solve semi-supervised learning problems where the data is not classified or unlabeled. There are some examples of principal component analysis, linear discriminant analysis, Sammon mapping, Quadratic Discriminant Analysis, etc.

I. Dimensionality Reduction Algorithms

It is the method of minimizing the larger size of data sets into most relevant user data, or it is used to minimize the unwanted noise signal which gives a high dimensionality numerous features that help to improve supervised learning for classification of data more appropriately. Some of the dimension reduction approaches are namely non-negative matrix factorization, auto encoder, principal components analysis, and random projection, etc.

J. Ensemble Algorithms

It is the combination of multi-learning schemes to boost up or improve the machine learning capability and accuracy. There are some examples like Adaboost, random forest, bootstrapped aggregation, gradient boosting machines, extremely randomized trees, gradient boosting regression tree, etc.

V. EVALUATION OF MACHINE LEARNING

In the machine-learning mission, the evaluation models are an important section. Both same types of machine learning and different types of machine learning mission have various evaluation indicators and each with different importance (classification, clustering, and regression) [48]. The classification results are described accurately by using confusion matrix which shown in table 1. It shows whether correctly classified or incorrectly classified and distinguishes classes for binary and n classification, i.e. 2*2 and n*n matrix [49].

Table 1 Confusion matrix [49]

	Predicted as Positive	**Predicted as Negative**
Positive Label	TP (True Positive)	FN(False Negative)
Negative Label	FP (False Positive)	T(True Negative)

The results for binary classification can be divided into four categories which are shown in table 1. The first one is true positive (TP) in which the model classifies only the positive samples. In True Negative (FN) only negative samples are classified by the model.

However, in False Negative, the model has misclassified the positive samples, and in false positive, negative data are misclassified by the model. The different performance metric is calculating using confusion metric is:-

A. Accuracy

It is calculated by the ratio of a number of accurately classified samples to the total number of samples taken for a given set of test data. If classes are measured or balance properly this is good measure and metric is useful or else it is not a useful metric. i.e. (TP+TN)/(TP+FP+TN+FN).

B. Precision

It is calculated by considering the ratio of correctly detected data to the actual detected items, i.e., TP/ (TP + FP).

Sensitivity (True positive rate): It used to calculate the ratio of all correctly detected data to the all what are the items should be detected; (TPR): TP/ (TP + FN).

C. FNR (False Negative Rate)

The ratio between the total numbers of misclassified positive items to the total number of positive items taken is FNR, i.e., FN/ (TP + FN). FPR (False Positive Rate): The ratio taken between the numbers of misclassified negative samples to the total number of negative samples. i.e. FP/ (FP + TN).

D. TNR (True Negative Rate)

The ratio between the true negative samples to the total number of negative samples occurred, i.e., TN/ (TN + FN).

E. F1 Score

It used to calculate the harmonic mean of precision value by 2*TP/ (2*TP + FN + FP).

VI. TRENDS OF MACHINE LEARNING TOOLS AND MATLAB USABILITY

The essential tools are must be able to do the multiple tasks at a time such as multiple incoming data processing, able to do the communication with the data sets while analysis of the results, it has a capacity to connect to the other software for sending and receiving the data, and the collaboration option would be there for user communication.

Thus machine learning tools are used in data analysists, visualization, and network modeling to design a suitable model. There are different kinds of machine learning tools are utilized to improve the performance of the system as well as to reach the user requires more vastly.

A. Sci Kit

It is one of the machine learning libraries for machine learning programming. This tool includes all ML model where linear and logistic regressors to SVM or random forests classifier. Also, it has to preprocess method toolboxes such as dimensionality minimization and feature selection, etc.

B. Tensor Flow

It is a software library provided in open source for numerical computation with greater performance. The architecture is flexible so that it allows easy computational arrangement over different platforms like CPUs, TPUs and GPUs, and from the desktop to edge devices or mobiles through the server. It is giving more support for both deep learning and machine learning, and more vastly using in scientific fields.

C. Mahout

Mahout is used to creating implementations of machine learning algorithms both scalable and distributed that are focused in the fields of 3 C's, i.e. classification, clustering, and collaborative filtering. It allows applications to evaluate large sets of data efficiently and in short time duration. Mahout algorithms work in a distributed environment as it is written on top of Hadoop.

D. Keras

Keras is a library written for Python. Keras is user-friendly, modular, and extensible and allows fast experimentation with deep neural networks. Keras reduces the number of events required for common use cases and also offers clear and actionable response upon user error.

E. MATLAB

Matlab is one of the most efficient languages for computing complicated mathematical equation or mathematical modeling for technical computation. Mathematical expressions like arrays or matrix can express easily compared to other languages like python instead of expressing through another generalized programming [50]. For example in python matrix math requires function call, unnatural operators and difficult to tracking various size of the array. However, in Matlab, it can show the computational mathematics very natural way. Python will give lack of reliability in scientific computing environments. So the scientist and engineers prefer Matlab language to work based on their requirements. Hence it Matlab is more efficient language to machine learning for predictive metrology [50]. Matlab toolbox will provide function and capability of whatever needed but python provide some authorized packages for the various operation of engineering, and it varies their quality and capability. So, Matlab will complete the task more easily, and accurately than with other custom programming language. It also helps to automate the whole path from research to production based on their workflow (appropriate implementation). In python, it requires overlapping and conflicting add-ons to get absolute performance. So, it concludes that the Matlab is a very faster programming language in data computation, visualization, and engineering calculation. It gives an appropriate route for machine learning to perform tremendously.

VII. MACHINE LEARNING APPLICATION TRENDS

A. ML Application Trends

Currently, many applications use machine learning as a base technology.

The machine learning technique contains many parts such as data classification, recognition, and prediction which are more applicable to data security, financial and marketing, business, etc. which makes the user easy hence it helps to reach the user requirements very vastly. Some of the machine learning applications are collected and briefly explained below based on the prior research efforts.

B. Multi-Label Image Annotation

The several existing research contributes an image application by considering multi techniques and algorithms. The work conducted by Ding et al. [51] has introduced the context-aware multi-instance multi-label learning method for image annotation. The method is providing different image annotation application such as video annotation, gene pattern annotation, sensitive multimedia detection and relation extraction in natural language processing. Similarly, the automatic image annotation is discussed in Sanghi et al. [52] where according to the given input keyword the image should be obtained. The KNN (K-Nearest Neighbor) algorithm is addressed to present a multi-label image annotation. The method is very useful in effective urban planning (water, land, residential area distribution). The same efforts are applied in Tian et al.[53] to overcome the annotation problem by addressing the multi-label learning technique and sparse representation. Also, the multi-label algorithm with posterior principle is proposed to obtain the unlabeled image tags. Sometimes the data sets contain unlabeled data with some labeled data, and weakly labeled data are also trained and learned for image annotation, the work is carried out by Wu et al. [54].

C. Face Recognition

The face recognition is used in security purpose, finding the human age, emotion recognition, etc. The study conducted by Li [55] has presented the face age recognition using Local Pattern Selection (LPS) Scheme. The method first based on LPS the intra user dissimilarity in the pattern is reduced, so based on the outcome the visual information at high-level information is collected. Hence the face aging information is obtained. The same kind of work face emotion recognition is presented using extreme Sparse Learning Method (ESLM) is introduced in Shojaeilangari [56]. The method contains extreme learning machine with sparse reconstruction character to provide an exact classification in the noisy region. The similar study is shown in Bouchaffra [57] to recognize an age-invariant face. Some of the case the face recognition is a difficult task in the various pose. So pose tolerant recognition presented in Abiantun et al. [58] by sparse feature extraction. The 3D generic elastic model and sparse extraction method are addressed to match among the non-frontal images of angle variation.

D. Speaker Recognition or Classification

The speaker recognition and classification in the different situation such as emotion, laughing, and speech, etc. are characterized using different techniques and algorithms. The research study of Dileep [59] has introduced the class independent Gaussian mixture model (CI-GMM) with intermediate match kernel (IMK) for classifying different length patterns. It performed well in speech emotion recognition as well as the identification of the speaker. The speaker verification research work conducted by Zhang [60] where SVM training and GMM used for feature extraction. It performed in both high and low-level speaker verification. The multi-speaker tracking task using SVM, and dictionary learning and identity model is presented in Barnard and Koniusz [61]. In this, the speaker tracking is done by considering some moving pedestrian datasets.

VIII. RESULTS OBTAINED FROM RESEARCH TRENDS ON MACHINE LEARNING

This section evolves with the discussion of collected data from IEEE publication. These data were cited from IEEE Xplore digital library on 4 September 2018 at 5:30 PM (IST). The research publication details from IEEE Xplore is obtained by giving keywords "Supervised learning" Type 1and "Unsupervised Learning" Type 2. The type-1 keyboard results give the existing research trends in machine learning with different technique adapted in supervised learning for classification, recognition, and prediction, while type-2 key results extend the existing research trends in machine learning of unsupervised learning with different techniques is used. The following figure 3 indicates the research trends in the IEEE publication. Similarly table 2 shows that the research trends in the IEEE publication in the tabular form.

Table 2 Existing Research Trends from IEEE Xplore in a tabulated form

S.I. No.	IEEE Publication	Supervised Learning	Unsupervised Learning
1	Conferences	6440	6721
2	Books	80	38
3	Journals and Magazines	1349	1342
4	Courses	3	1
5	Early Access Articles	99	59

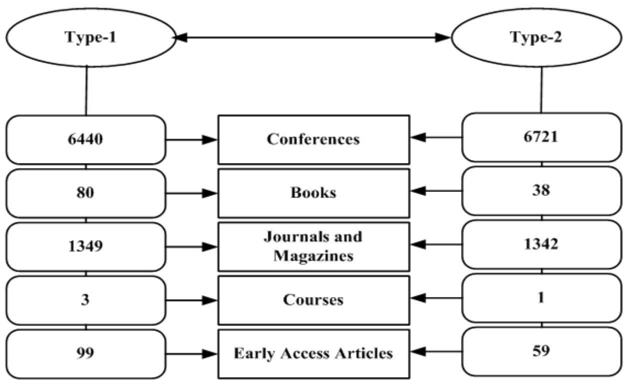

Fig.3 Existing Research Trends from IEEE Xplore

It is observed that the type-1 research trend exhibits 6440, 80, 1349, 3, 99 publications with conferences, books, journals and magazines, courses, and Early Access articles respectively. The type-2 research trend has 6721, 1342, 59, 38, 1 publications of conferences, journals, and magazines, early access articles, books, and courses.

IX. RESEARCH GAP

Few Benchmarked Studies: Few kinds of literature are found to perform benchmarking with extensive simulation and comparative analysis.

Benchmarking gives an insight into the performance efficiency of a proposed approach, and it's superiority as compared to the state of art baselines.

X. CONCLUSIONS

This study describes the best machine learning methods, algorithms, and mechanisms which is suitable for solving the different kinds of issues. The recent prior research works of machine learning with various schemes and their exhibited efficient as well as limited outcomes are discussed in the literature study part.

Based on the evaluation criteria the methods perform well in order to provide a prediction, segmentation and classification which are briefly explained in the present investigation study.

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