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An Ensemble and Dynamic Ensemble Classification Methods for Data Streams: A Review

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***Abstract*— Data streaming is the transmission of a continuous data stream which is often fed into stream processing software to produce insightful data. A collection of data elements arranged chronologically make up a data stream. The two methods used to classify data streams are single and ensemble classification. The single classification technique is quick and uses less memory for processing, but as the number of unknown patterns or samples rises, its efficiency declines. The ensemble technique can be utilized for two main reasons. Compared to a single model, an ensemble model can perform better and result with accurate predictions. Ensemble learning (EL) generates various base classifiers form which a new classifier is produced that efficiently performs than other traditional classifiers. In addition to the algorithm, hyperparameters, representation and training set, these base classifiers may differ in the type of classification. A dynamic ensemble learning (DEL) is a sort of EL algorithm which automatically selects the subset of the ensemble members while making the prediction. The primary benefit of DEL is improved predictive accuracy when compared to normal EL. This paper study and analyse various dynamic ensemble classifier model for data stream classification. The identification of merit and demerit of these methods help to understand the available problems and motivate researchers to find out new solutions for the listed problem.**

I. INTRODUCTION

A countable infinite series of elements makes up a data stream. There are various data stream models that adopt various stances about the mutability of the stream and the structure of the stream parts. Stream processing is the process of analysing data streams as they are being generated in order to provide relevant output as new input data becomes available [1]. Stream classification is a subset of progressive training of classifiers which must satisfy the conditions particular to enormous amount of data streams like constrained processing time, and memory, and a single view of incoming samples. It is common for stream classifiers to operate in dynamic, non- stationary scenarios where input and target principles may change over time. It is difficult to process an existing data while current data constantly occurs in the data-stream Ease of Use classification process. A low computation time per data element will always ensure low computation latency, and the algorithm will not be able to match the data stream if computation time per data element is high. Simple data-stream classification model is shown in Fig.1.

EL model is efficient decision-making process which often occurs in supervised machine learning (ML) applications. A base-learner or inducer is a technique that takes a set of annotated instances as input and produces a result as a classifier or regressor which generalises these samples. For new unlabelled instances, predictions can be made using the generated framework [2]. EL are learning algorithms that provides a collection of classifiers and then categorise new data by getting the vote (weights) of the respected classifier predictions. The Bayesian averaging-based ensemble approach is still used in recent days, although more contemporary algorithms like boosting, bagging, and error-correcting output coding have also been developed [3]. The sample ensemble model is shown in Fig. 2.

In EL, a machine-learning utilizes multiple base learners to form an ensemble learner for the achievement of better generalization of learning system, has achieved great success in various artificial intelligence applications and received extensive attention from the ML community. However, with the increase in the number of base learners, the costs for training multiple base learners and testing with the ensemble learner also increases rapidly, which inevitably hinders the universality of the usage of EL in many artificial intelligence applications [4].

Stream classification is a subset of incremental learning of classifiers that must meet limitations unique to enormous streams of data: constrained memory, constrained processing time. Ensemble based approaches are the frequently utilized techniques methods for classifying the data streams. Their prominence can be attributed to the fact that they outperform powerful single learners while being very simple to implement in practical applications. The integration of drift identification methods and the incorporation of continuous upgrades, such as the selective deletion or modification of classifiers, make ensemble techniques particularly beneficial for data stream learning [5]. As a result, the ensemble would function better overall in making predictions than an individual inducer. This paper discusses about different EL models for Data streams using ML and DL methods for increasing the accuracy of DataStream classification. It also focuses on the merits and limitations of these models to suggest further improvement on EL.

The remaining section of this paper is organised as: recent methods for ensemble classification for data stream are covered in Section 2 of this article. Section 3 examines their advantages and disadvantages. The conclusion and future scope are discussed in section.

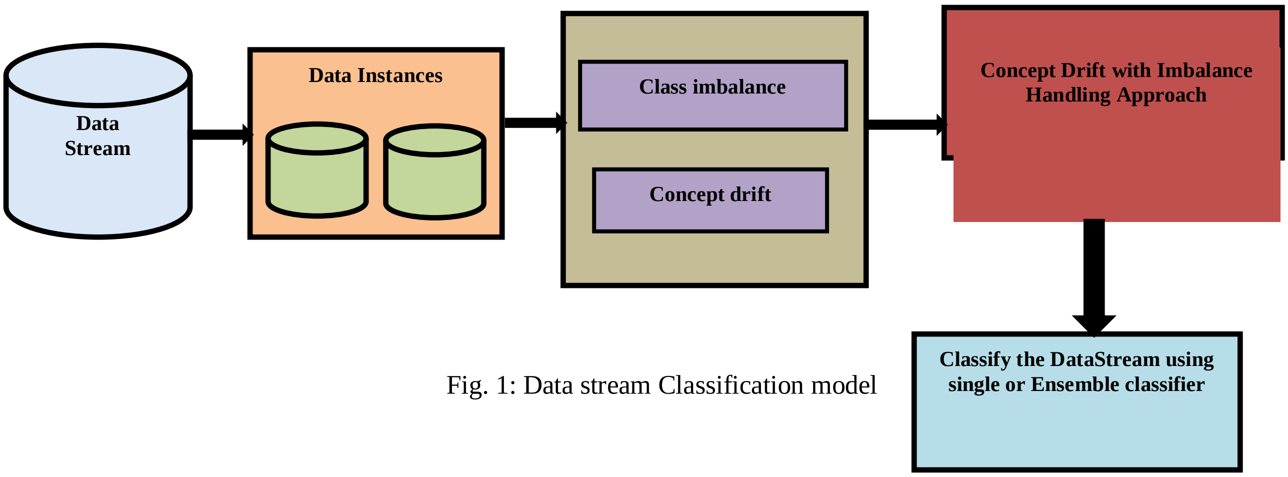

Fig. 1: Data stream Classification model

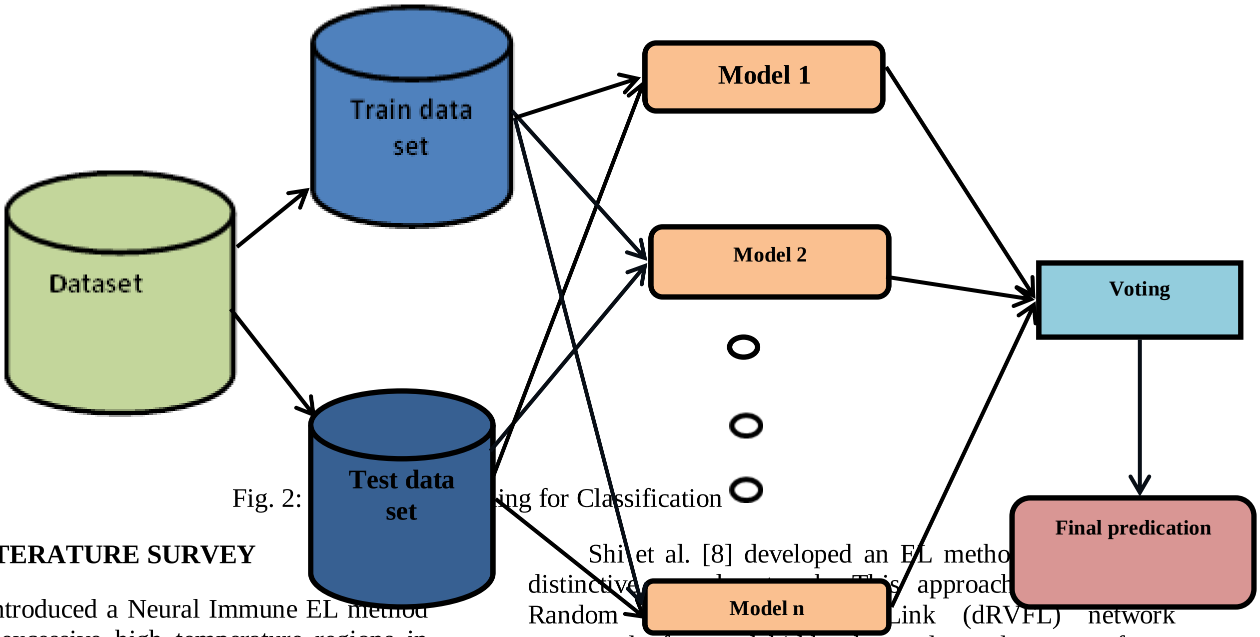

Fig. 2: … ing for Classification

II. LITERATURE SURVEY

Yu et al. [6] introduced a Neural Immune EL method (NIELA) to detect excessive high temperature regions in infrared steam pipeline images based on EL theory and the integration among the nervous and immune systems. This method effectively extracts the pipeline stage in the complex background environment, automatically extorts the features and establish a classifier to detect the deviant high temperature region to overcome the subjective factors with high accuracy rate.

Bakhshayesh [7] developed a heterogeneous EL algorithm to resolve the dependency problem of estimated accuracy on the different feature selection (FS) techniques. In this algorithm, the Neighborhood Component Analysis (NCA) and Relief were considered as a FS algorithms whereas bayesian regularization (BR) and Levenberge Marquardt (LM) were considered as learning algorithm of feed-forward neural network (FFNN) for evaluating the nuclear power plants (NPPs) parameters. Various integration methods like Min, Median, Arithmetic mean, and Geometric mean were used to ranking the features. The target parameters might be estimated with more accuracy and dependability by using this method.

Shi et al. [8] developed an EL metho… distinctive … This approach … Random … Link (dRVFL) network composed of several hidden layers layered on top of one another. This dRVFL network would extract rich feature information through a number of hidden layers that were formed randomly within a suitable parameter in which resulted weights were calculated by the confined algorithm, as in a typical RVFL structure. An EL and DL were employed to produce an edRVFL method. In order to effectively retrieve crucial data from sparse input, edRVFL techniques could be learned only once separately from scratch.

Cruz et al. [9] introduced a technique for producing a neighbor-optimal ensemble of Convolutional Neural Networks (CNNs) by employing an effective search method based on an evolutionary method. The voting policy and the network architecture were incorporated into the of CNN ensemble layout which was fine-tuned using this ensemble method. This method was tested in a practical industrial setting by identifying metal sheet misalignment and integrating it with submerged arc welding. This technique considered more suitable strategy to generate more integrated response.

Shahabia et al. [10] developed a transfer learning (TL) approach using pre-trained CNNs in order to predict the effectiveness of antidepressant medication for patients with Major Depressive Disorder (MDD). This approach utilizes time-frequency images acquired from the wavelet transform (WT) with resting phase of electroencephalography (EEG) signal. With limited dataset, this method effectively adjusts and fine-tunes the network weight to the objective task. At last, the EL model with majority voting of the outputs improved the efficiency to categorise MDD individuals as antidepressant responders or non-responders.

Tanga et al. [11] introduced a concurrent EL technique based on local binary patterns (LBP) and CNNs for face identification, LBP was first utilised to analyse the face structure of the input images, and then CNN was employed to extract the facial attributes from the LBP-processed images. At last, the concurrent EL technique was used to find the desired face recognition result by majority voting. Additionally, this parallel EL technique was developed to enhance the CNN's poor generalisation performance imposed by the learning process becoming trapped with a local minimum and to enhance the effect of facial recognition.

Folino et al. [12] proposed a novel ensemble-based DL framework for Intrusion Detection Systems (IDSs). In order to deal with the non-stationary nature of IDS log data, an ensemble of specific base deep neural network (DNN) classifiers trained on discontinuous portions of the data instances' stream with a combiner model was developed. An ad-hoc shared DNN model was adopted by combining a features of dropout mobility's, delay-relationships along with a cost-sensitive loss to train the deep base classifiers effectively on unbalanced datasets.

Wen et al. [13] designed an EL framework with DNN to detect the time-series for non-linear system. Initially, a different non-linear systems with various learning systems were used to record the discrete value and remove uncertainty difficulty for the detection. The K-means algorithms was used as a pre-processing technique and hypothesis verification to improve the prediction accuracy. The forecasting models were developed to detect the value of time steps. The Mean

Average Error (MAE) was developed to estimate the accuracy and eliminate the detective errors.

Bargshady et al. [14] developed a new model that integrates hybrid, Ensemble DL model, CNNs to collect facial image characteristics to identify and categorize the pain. In this model, the VGG-Face was modified and combined with principal component analysis (PCA) to gather images attributes from the multiple severity pain database in initial stage of model integration. CNN and recurrent neural network (RNN) algorithm were developed to classify images features based on the pain stages. The ensemble DL model was used for training and testing purposes with datasets obtained with different pain features.

Aversano et al. [15] developed a new EL approach for efficient COVID-19 identification using CT scan images. In this approach, TL was used to categorize the grouped lung lobes images using pre-trained deep networks generated with a genetic algorithm and integrated into an ensemble structure. Then, a voting strategy was utilized to find the decisions by using the outcomes of the single classifiers. This approach was very efficient to utilize in the medical domain especially in the covid-19 detection cases due to their wide search space with large number of parameters.

Jian et al. [16] presented DNN model with EL methods to reveal missing logs more accurately. This model integrates multi-variable linear regression (MLR), DNN and bagging and boosting type ensemble model for revealing local or global co-relation from training data. Loss operation among the detected values and supervised target values was introduced for the training procedure. The pre-training DNN model was used to train knowledge of data with two geographical layers. With the trained knowledge, the final layer of the network was fine-tuned to enhance the performance for missing well log prediction.

Ayan et al. [17] created a weighted ensemble of deep CNN based on genetic algorithms to identify insect species. Initially, TL methods were used to train the pre-trained CNN models on several insect databases. The EL method was then constructed using three distinct models with high estimated accuracy. After that, the models ensemble weight were obtained by voting approaches which integrates the output of the CNN models and relative weights to efficiently identify insect species.

Liew et al. [18] developed an EL technique for distinguishing colonic polyps based on various modified deep residual networks (DRNs), PCA, and AdaBoost-EL algorithm. A sophisticated DRN model (ResNet-50) was examined to lessen the computing time by modifying the model's structure. The endoscopic images were used to learn the categorization model by utilising median filter, image binarization, contrast adjustment, and normalization approaches to minimise interference problems. In addition, AdaBoost-EL algorithm was learned on the principal element of feature extraction with the collected labels from training datasets to identify polyp non-polyp outcomes.

Zhang et al. [19] presented a new ensemble support vector RNN (E-SVRNN) to generate more effective and accurate EEG signal categorization performance. Initially, the support vector machine (SVM) was used to generate the model for identifying EEG signals. The SVM description was then converted into a convex quadratic programming (QP) problem. The convex QP problem was then solved by employing a varied polynomial RNN (VPRNN) structure with a cost function. The E-SVRNN framework might upgrade all variables simultaneously due to the network which was integrated with complete connectivity mode. This model would be efficient to utilize in large data applications to increase the effectiveness of parameter solution.

Cannizzaro et al. [20] developed an EL methods to forecast Global Horizontal Solar Irradiance (GHSI) in short- and long-term time-horizons using various meteorological time-sequence data. In this model, variational mode decomposition (VMD) and CNNs were combined with Random Forest (RF) or Long Short Term Memory (LSTM) to detect solar panel results. Finally, these results were post-processed for the final GHSI prediction.

Niyas et al. [21] suggested radical ensemble selection of classifier to detect healthy, mild cognitive impairment, and alzheimer's disease patients. The medical scan outcomes, cerebrospinal fluid, cerebral defacement, and demographic data were gather from the patient's health examination report for the purpose of disease detection. ML classifiers were used as input for the radical ensemble of classifier selection strategies in order to efficiently classify Alzheimer's illnesses.

Guo et al. [22] developed an ensemble-based online modified DNN model to broadcast data with concept drift. Initially, the adaptive depth section was introduced by integrating inadequate features with depth features which frequently adapts to the variations of input at subsequent times to manage the information transit in the neural network, improving the completion of the online DL model. Then, the adaptive depth section of various layers were depicted as the classical classifiers for ensembling and weighted dynamically according to the loss of each classifier. Moreover, a radical decision of base classifiers was employed in response to the variations in the streaming data in order to strike a balance between flexibility and stability.

Al-Daweri et al. [23] presented a divergent EL based dynamic ANN classifier to resolve the issues of IDS. In this model, the dynamic ANN (DANN) was enhanced by utilising a simplified discrete cuttlefish technique and a filter-wrapper approach (CFA). CFA (discrete CFA) were augmented with a rough-set theory-based constructive heuristic to develop a filter-wrapper technique for feature selection and ANN structure optimization. Then, the CFA (migration-strategy based CFA) was utilised to improve the weights and biases simultaneously during the wrapper process in conjunction with the improvement of observed data and ANN topology.

Thiago et al. [24] introduced a heterogeneous and dynamic ensemble selection (DES) model comprised by a regressor groups which were continuously chosen by classifiers. In this model, a set of regression techniques was learned using the training and testing data’s in the training phase to validate the models. Then, specific classifiers identified the appropriate regression prototype for every training instance through training. In the testing phase, each trained classifier was used to automatically select a regressor prototype from the pool in order to predict the effort required for each test instance. These predictive integrations brought out by the classifiers selected repressors yields the final prediction.

Zou et al. [25] developed DES strategy to promote an efficiency of Error-Correcting Output Codes (ECOC) algorithms. In this algorithm, every column of coding matrix was linked with a collection of feature subsets chosen using different feature selection techniques. An innovative criterion based on the data difficulty concept was used to select an ideal feature subset from the candidate subsets during the decryption process to differentiate unidentified samples effectively. This strategy could be incorporated with any ECOC algorithm to detect the minority labels and eliminate class imbalance issues effectively.

Wang et al. [26] developed a dynamic EL to identify an outlier for complicated nonlinear industrial systems. In this model, the decision template was used as the integration technique. This method utilizes a shifting strategy based on quantitative tests to select whether to employ a decision template or a one-class classifier when making a vote in a particular position. Weaker base learners might be eliminated from the ensemble for the relevant test point using this dynamic selection technique. By using the bias-variance trade-off, this method lowers bias and enhances the ensemble performance.

Chen et al. [27] presented a DES wind speed detection method using hybrid deep reinforcement learning (DRL). Initially, a deep echo stage approach supplemented by practical wavelet packet decomposition was utilised to traditional models with diminishing prominence. Classical classifier weights were computed by using a multi-objective optimization methods. The bias and variance of ensemble models were simultaneously reduced to boost generalizability. Non-dominated integration weight solutions were combined with a DRL structure to achieve dynamic selection. By precisely constructing the reinforcement training setting, it would continuously identifies the non-dominated solutions in each forecast based on the time-varying parameters of wind speed.

Wang et al. [28] developed a dynamic ensemble outlier identification technique by single- label classifiers base learners. In this model, an adaptive k-nearest neighbour (AKNN) was used to explore the local region in order to construct the validation set for each test pattern. This AKNN technique utilizes the support vector data description (SVDD) method to explore the local region where label dependent possibilities were not persistent in relation to the matching test pattern. A probabilistic model which utilizes the posterior probabilities of single classifiers was determined to produce the classifier competences for effective outlier detection.

III. COMPARATIVE ANALYSIS

In this section, a comparative analysis of different methods used for EL and Dynamic EL process is presented. Table 1 gives the merits and demerits of EL and Dynamic EL methods which are studied in above section.

Ref. No.	Methods	Merits	Demerits	Dataset Used	Evaluation Metrics

[6]	RF ,CNN NIELA	Precise identification of high temperature pipeline area	Number of images taken for analysis was limited.	13 infrared pipeline, Fluke Ti32 infrared camera.	Accuracy for RF= 90.13% ,CNN= 96.50% , NIELA= 98.38%
[7]	FFNN-BR	This method was direct and practical, providing more precise and trustworthy results.	Lower performance on larger datasets	Synthetic dataset	Average Mean Relative Error AMRE = 0.98 Cumulative Distribution Function (CDF) = 2.44
[8]	edRVFL	These methods have high training efficiency.	High cost of computational time	46 tabular UCI classification datasets, 12 sparse datasets.	Avg. rank=4.16
[9]	Evolutionary algorithm	These methods have more appropriate strategy to generate more integrated response.	Designing an effective ensemble becomes more difficult when establishing the best practical voting policy.	1000 image datasets.	Accuracy= 97.8 %
[10]	CNN, TL.	Advantages as a result of its low cost and ease of setup.	The limited amount of training samples were used	Resting-state 19-channel EEG recording of 60 subjects in eye-close (EC) situations is 30 subjects.	Accuracy= 96.55%, Sensitivity= 96.01%, Specificity= 96.95% F1-score = 96.41%.
[11]	LBP, CNN.	Efficient security coefficient, easy data collection, and straight forward popularisation	Use large number of network parameters and high computational complexity.	Yale-B dataset consists of 38 patients with 576 face images per person in 9 postures and 64, ORL dataset constitute of 40 patients with 10 face images per person.	Accuracy for CNN= 96.3%
[12]	DNN	Using a loss function would produce a cost-sensitive issue	Having many unlabelled data. Labelling a lot of data can be expensive	CICIDS2017 dataset, ISCX IDS dataset.	Accuracy= 0.9136, DR=0.9838, FAR= 0.1200.
[13]	RCM, OVM.	Smooth nonlinear systems can be efficiently handled using method	Poor performance with unstructured noisy signals	More dimensions or quantize the datasets.	Accuracy= 1.000
[14]	EDLM	This technique was well-suited for real-time applications in the fields of medical informatics and diagnostics.	Adding more network layers can significantly enhance the size of the retrieved image features	MIntPAIN and UNBC-McMaster Shoulder Pain datasets.	Accuracy for EDLM =92.26%
[15]	Novel ensemble-based approach	The ensemble's performance was quite stable for the combined dataset.	Small number of datasets were used to create the combined dataset which lowers the model's efficiency	Scarcity of large and well balanced datasets.	Accuracy= 99.4%.
[16]	Traditional ML method	Easy to train the model with computational burden	This method was not suited to deal with low-quality, incompact data.	Bootstrap datasets.	PCC =0.8652, MSE=0.001979.
[17]	CNN	This method achieves very high	This method contains larger number of	Small dataset with 10 classes and IP102	Accuracy=89.30

		accuracy in image recognition problems.	incompact data, which could lower the performance efficiency	dataset with 102 classes, D0 datasets.	
[18]	Novel approach, AdaBoost EL.	The model's performance was improved while its computation time would be reduced.	The model's efficiency was increased while it's computing time also increased.	Kvasir dataset.	Accuracy=99.10%,sensitivity=98.82%,, precision=99.37%, and specificity= 99.38%
[19]	E-SVRNN	More efficient and light-weight method	It can be challenging to train. Processing lengthy sequences gets highly arduous if you use the activation functions.	Public dataset IIb of BCI Competition II and dataset II of BCI Competition III.	Accuracy =99%
[20]	GHI	This method efficiently utilizes sophisticated metric for predicting solar panel output	Because it only permits short-term Prediction.	Six years of meteorologialdata.	RMSE for RF= 107.415
[21]	Dynamic Ensemble Selection of Classifier algorithms.	Dynamically assigning a range of various classifiers to test the data	Difficult to train the model and results with more classification errors.	ADNI-TADPOLE, global challenge Dataset.	RF=80%, ET=78%, ADABOOST=73, BDT=80%.
[22]	Deep learning model.	This model was resulted with high accuracy and stability.	This technique struggle with concept drift	Synthetic datasets, Real-world datasets.	Accuracy= 1.30
[23]	Cuttlefish Algorithm	Handle large amount of data accurately	High dimensionality problem	GPDL dataset, KDD99 dataset, KDD99 dataset.	Accuracy= 97.52% , DR= 99.93%, FAR= 13.13%.
[24]	DES	Increased robustness.	Implementation was still limited in the industry.	sixteen data sets	Accuracy Mean Relative Error=3.19.
[25]	ECOC	The model have high accuracy and stability.	High cost of computational time.	UCI data sets	NB=15, D Tree=33, KNN=35, LR =37, SVM=25.
[26]	Outlier detection method, dynamic EL	This method was stable and efficient to provide linear results	This method was extremely difficult to handle the situation of outlier detection	10 data sets from KEEL 2 repository.	Accuracy G – mean= 92.12%
[27]	KNN algorithm	This method provides stable predictive result for all classification	This approach was acquired with high computational complexity	Pareto front of four datasets.	MAE=1.7701, RMSE=2.8788, PCC=0.8450
[28]	KNN algorithm	Robust approach, efficient outlier detection.	lack in ground truth makes outlier faulty detection	20 data sets from UCI Repository.	AVR=6.00, SB=6.80

Table 1: comparison of EL and Dynamic EL process

Form, the above table, the article [6-28] is studied and it is Concluded that the article [6] yields good efficiency and better article [6] NIELA is based on the coordinating function of the neurological and immune systems in the human body. Based on the properties of the infrared pipeline image, the algorithm utilized in this work will effectively diagnose the defects in the pipeline area more accurately. The same algorithm can be used for any type of data stream classification. But, EL for various dataset can be decided by algorithms efficiency and dataset characteristics.

IV. CONCLUSION

In this article, a survey on recent EL and DEL methods is analysed including with their merits and demerits. Through this comparative analysis, the EL ensures that the final predication results are reliable and accurate However, the most time expensive computation comes from the in this techniques. Future study will necessitate additional research to address these concerns by applying sophisticated methodologies that could effectively improve the effectiveness of EL and DEL systems.

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