Identifying the Interest of Learning from Adult Learner Using Machine Learning

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Abstract-The process of learning is continuous which will continue lifelong. This is potentially an essential tool for human survival and environment adaptation in both internally and externally. When instruction is catered to a learner's physical and mental capabilities, learning plays an important role. Adults are driven to learn for different reasons whereas the students expand on their prior learning and experience. Adults have a strong desire to take control of their learning and develop their own interests. The program's beneficiaries are adult learners, and without their participation, the initiative cannot succeed, wasting money, people, and other material resources which is not confused to reveal in sending people to the moon and accomplish fantastic possessions but this nation forgot to understand that the adult illiterates can able to render illiterate rate quickly. Teaching adults in the centers has become a monumental task. Adult education benefits from educational psychology's broader applicability, which encompasses learning theories, interest, memory, forgetting training transfer, theories of teaching, attitudes, skills, and environment. Therefore, this research concentrates on detecting the interest of adult learner using Tree-based Pipeline Optimization Tool (TPOT) for Automatic Machine Learning (AutoML) in the dataset collected from the Adult Learner Center in Tamil Nadu, India. Based on this pipeline, the resulted accuracy is better in Stochastic Gradient Descent (SGD) classifier while compared to another classifier in the TPOT for AutoML.

Keywords: Adult learner, education, Machine learning, TPOT, AutoML, learner interest

Introduction

The most effective learning occurs when the material is catered to the learner's physical and mental capabilities. Each learner involves various learning requirement and it is crucial for teachers and staffs to understand their students well. Adult learners cannot use the same pedagogical ideas that apply to children. It is not appropriate to treat the adult learner like a grown-up youngster. The quality of life for older persons has received a much attention as a result in ageing global population [1]. The educational approach has been shown to be one of the greatest and most successful methods for assisting senior citizens to get involved and interact with society, enabling them to live happier, higher-quality lives [2]. Ageing and psychological changes are closely intertwined, especially when it comes to cognitive impairment. Due to changes caused by ageing, such as losing control over their movement, perceptual, and even cognitive control, older persons may experience difficulties and hardships when interacting with these interfaces [3].

Learning can be done as a full-time learner or part-time learner during this process. This may be self-mentored or sponsored by a company. Adult learners are made up of a variety of people from different genders, classes, religions, castes, locations, major or minor groups, racial groups, and ethnicities who differ from each on the basis of their requirements, issues, demands, perspectives, and views on life. The learning environment for adults is intentional and independent of children's interests. Adult learners may stop participating in learning procedures if their requirements aren't satisfied since they are extremely clear about the outcomes, they hope to achieve from the learning process. According to research, adult learners frequently take on more duties and responsibilities than a conventional student, which affects their general academic outcomes [4] [5]. Depending on their particular circumstances, adult learners play a variety of responsibilities, such as parent, worker and carer. Adult learners may ignore their assignments and eventually drop out due to their incapacity to attend lessons on a regular basis or a lack of time [6]. Those with dependent children are the adult learners most susceptible to dropping out.

The ability of an adult learner to continue their education in a higher level depends on their financial situation. This component varies among countries depending on the level of financial assistance given as well as the personal circumstances of the individual [7]. Due to the conflicting pressures of work and school, adult learners who are compelled to pursue employment but are not qualified for financial assistance are at danger of quitting out [8] [9]. When there is little overlap between their former experiences and their current position as students, adult learners may find it challenging to transfer into higher education, which may affect their continued engagement [10]. Adult learners' involvement in higher education is crucial for their psychological as well as social growth, but obstacles to their continuous engagement are created by external environmental factors including family and employment obligations. Despite the fact that unconventional learners are a demographic at risk for academic failure and have a higher possibility of dropping out, they can still graduate from college and pursue careers. There is a larger possibility that adult students will graduate from higher education if they approach their studies with a cooperative and attentive attitude and seek out assistance when needed [11] [12].

Motivation is a term used to describe an organism's interaction with its environment and to explain why it behaves in certain way it does. Research on the motivations of older individuals normally falls into three primary divisions that were previously discussed in this section. Motivation has been studied from a wide range of viewpoints. To explore the motivations of older adult learners who participate in education, one area of research bases or modify Houle's and Boshier's typologies. The second branch of study employs a number of theories that have been proposed to explain adults' desire to take part in education, along with performing empirical studies similar as the first branch. The motivation of adult learners (nontraditional students) is the subject of the third study branch, which is obtained from a psychological viewpoint. Intrinsic and extrinsic motives are typically defined in this field of study. In contrast to the third branch of study, which is drawn from a psychological perspective and looks at learners' motivation to learn, the first two areas of research are prone to explain why people take part in education. In the last part of the study, the researcher suggested an integrated concepts to investigate older adult learners' motivation from the viewpoint of their own motivation in order to understand grown up adult learners' inherent ability to concentrate their energies and attention in the course of learning. This section also took into consideration of both literature review and actual scenario of elderly adult learners.

ML is often defined as an area of expertise that enables computers to understand without being specifically programmed." Contrary to popular belief, skilled ML professionals are aware that creating efficient ML pipelines can be time-consuming and frequently requires extensive ML algorithm expertise, domain knowledge, and time-consuming the brute force exploration method. Researchers have been working on a TPOT for the past few years that automatically develops and improves ML pathways for a particular issue area [13] without requiring human input. In essence, TPOT automates the creation of computer programs by optimizing ML methods utilizing a variation of the evolving computing method known as Genetic Programming (GP). However, the precious study illustrates that GP and Pareto optimization work together for allowing TPOT to routinely build high accuracy as well as compact pipelines and regularly improve simple ML studies [14]. Hence, this research focuses on ML methods to build an effective model to detect the interest of the adult learner for providing them certain rewards and conducting programme to develop their skill better and even provide addition support to improve the interest to the adult learner.

Literature Review

Activities for adult education should be focused on addressing both the environments and people educational needs. To become better citizens, people need to be workers and family members, even the people need to master a wide range of abilities. People's full potential and sense of personal contentment can be reached by participating in adult education programmes that provide the knowledge, skills, and information they need. These programs are appropriate for society and beneficial to the individual. This literature has supported to identify the need and interest of adult learner for improving the skills to develop themselves. There are various ML models to identify the interest through the features involved in the datasets are disused in this session.

According to the preliminary findings of Fensie et al, there is a dearth of research on the learning process of adults enrolled in distance education. The majority of the literature relies on learner's opinions and contentment as its primary data source and some articles offer suggestions for interacting with adult learners in distance learning without providing any actual evidence of such recommendations. The two main categories used to characterize and assess the adult learners' learning processes are language learning and continuing medical education. The ultimate inclusion criteria for scoping reviews must be decided after several iterative evaluations of searches and presentations. The knowledge and expertise of numerous many people helped this team during this process, which resulted in a more thorough examination and a broader grasp of the literature [15]. As a result of the recent worldwide epidemic, Garret et al, employed the distant education has become more widely known. Understanding the current status of observational and theoretical studies on adult learning in remote education is becoming increasingly important due to the growing number of nontraditional learners and the disruptions to learning caused by world events [16]. There are several demanding roles for adult learners. Additionally, Sun suggested that, they need to learn how to study distantly and re-adjust to the demands of learning. It is projected that adult learners would change the procedures and regulations in higher education as they become a more significant presence in the sector [17].

Palacios et al discussed about the Student Performance Prediction (SPP) which attempts to predict a student's performance before participating in an educational programme or taking a test [18]. Snjeˇzana Kriˇzanic discussed about data collection, formulation of the issue, practical applications, employed techniques and prediction the objective are the five data mining phases that will be used to accomplish this. Online, offline, and blended learning are the three main types of education that have been offered. The goal of the data analysis approach known as "data mining" is to uncover hidden knowledge in the source data. On the educational data of Croatia's higher education institutions, the Data Mining (DM) techniques such decision trees and cluster analysis are used [19]. Students are grouped together as a result of cluster analysis, while deeper grouping analyses are performed using decision trees. Another DM method proposed by Tismy Devasia et al, categorization is employed in Amrita Vishwa Vidyapeetham Mysore to forecast student division based on historical data. More accuracy is offered by the mining strategy of naive Bayesian to the extraction of meaningful information from data [20]. Student academic background is taken into account. According to research by Wang et al. on the level of automation needed by data scientists, creating an AutoML tool with a "human in the loop" is preferable to one that fully automates ML tasks [21]. Drozdal et al. conducted qualitative research to determine what factors influence trust in ML models created with AutoML tools. They discovered that data scientists have more faith in AutoML solutions where non-functional criteria like model performance measurements, transparency and visualization are included [22].

Li et al, proposed about the earlier techniques which combined these with the hyperparameters of relevant algorithms to create a single hyperparameter vector by viewing the selected option of a technique as another other hyper-parameter, which is a binary value set to 1 if the appropriate algorithm has incorporated in the pipeline. This reduced the CASH issues in a Hyperparameter Optimization (HPO) problem. One advantage of this reduction is that it makes the original issue amenable to well-known HPO techniques like SMAC, which is based on Bayesian optimization, Hyperband (BOHB), which is dependent over a multi-armed bandit method or BOHB, which combines the two [23] [24]. Le et al, introduced a Python-based AutoML tool called

TPOT employs genetic programming in identifying the best ML pathways for either categorization or regression on a provided (labelled) dataset [25]. In a nutshell, TPOT conducts Generalized Projection (GP) on trees, whose nodes are made up of operators and each of them belongs to one of the following four operator's category such as

1. Decomposition functions
2. Feature selectors
3. Preprocessors
4. Estimators

This is used to perform as classifier and regressor whereas predictions have produced from root node and similar copies of an input data get into the tree with leaf nodes. As "branching points" in the tree, some operators such as selectors of feature set as well as model selectors that receive input from many preceding operators. Numerous free parameters for each operator are optimized throughout training. High performance and minimal model complexity are both balanced by TPOT. As a result of this, the pipelines that TPOT learns have a relatively low operator count but perform as well as or better than competing state-of-the-art by ML methods. Stacking Estimator components can enable estimators such as regression or classification models in transmitting their outputs as "synthetic features" to succeeding operators are a crucial part of TPOT.

The effectiveness of instructional approaches created for older persons in mastering digital technologies is a research gap that exists in the available studies. Despite the fact that many studies have addressed this topic, there haven't been enough comprehensive assessments of the previous research. The development of specific questions to aid in the production of pertinent evidence was done through a systematic review. Through the aid of a data extraction tool, specific information has been identified by conducting a search among designated databases using precise key terms. Simultaneously, there are a number of reliability and quality problems with a standard literature review. This research makes an effort to advance knowledge through conducting a comprehensive literature assessment of the efficacy of instructional techniques that have been created for adult learners utilizing TPOT and AutoML approaches.

Research Methodology

Modernized technology can now increase older persons' autonomy as well as life quality by enabling them in developing and sustain social bonds, gain access for caring and services, advance their lifelong learning initiatives, and have fun and amuse themselves. The use AutoML technique in this research have assist in identify the interest of adult leaner for the collected dataset. This research focuses on identify the skills of the specific adult learner as well as their interest of learning method to encourage further for development to lead an educated life. Generally, TPOT has designed as an AutoML for performing specific task. Invoking tree based AutoML tool has been implemented with various classifier. The optimization pipeline associated with tree type model is utilized for performing the analysis in identifying the interest of adult learner.

Dataset collection

The dataset is collected from adult learner center in Tamil Nadu, India in which old learner are 249 members with age range from 30 to 57 years. The learner's employment involved are driver, agriculture and certain learners are unemployed. The interest of the ICT tools involved in this research are Mobile and laptop. Moreover, there are certain qualitative analysis from the staff also considered in this research to evaluate the learner's interest. Thus, the evaluation of the adult learner is identified through scores obtained for the questionnaires are

- Q1 – I am interested to learn through
- Q2 – When learning from the Internet, I would like to read from
- Q3 – When learning from the book, I like
- Q4 – I like a teacher, who uses
- Q5 – When I am having doubt, I prefer
- Q6 – During my free time, I most enjoy

	NAME	GENDER	AGE	QUALIFICATION	EMPLOYABILITY	ANNUAL SALARY	Children Education	STUDY TIME	MODE OF STUDY	ICT TOOLS(Interseted)	...	5.2	5.3	5.4	5.5	I am Interested to learn through	When learning from the Internet, I would like to read from	When learning from the book, I like	I like a teacher, Who uses	When I am having doubt, I prefer	During my free time, I most enjoy
0	Somesh V	M	38	No	Agri	9000	Educated	1	Book	Mobile	...	1	1	2	1	4	3	4	4	4	3
1	Vedika	F	47	No	Agri	7000	Educated	20	Book	Mobile	...	2	3	3	2	3	3	3	3	4	4
2	Kannamma	F	44	No	Driver	7000	Educated	0	Book	Laptop	...	2	1	2	1	3	1	2	3	3	3
3	Meenakshi	F	42	No	Unemployed	0	Educated	0	Book	Mobile	...	3	1	3	1	2	3	3	2	2	2
4	Pranitha B	F	53	6	Unemployed	0	Uneducated	0	Book	Mobile	...	4	2	4	2	1	2	1	2	1	1

5 rows × 36 columns

Figure 1 Dataset for adult learner

Working of AutoML with TPOT

The practice of fully automating an application of ML to actual problems is known as AutoML. The primary issue with AutoML is that proposed algorithm must discover an appropriate set of operations to each step in the ML pipeline for eliminating the bias. According to analytical, AutoML has been illustrated in equation 1.

$$O_P C_{O_S} + 2^{N.G(f1,f2)} P_{N_{Max}} + \sum_{m' \in Max} \sum_{r \in R} P\left(\langle m'.r\mathrm{I}m\rangle P\big(r + y.v(m')\big)\right)$$

(1)

Where,

O_P = Pre-defined operation set as default

O_S = Selection of operations based on algorithm

$G(f1, f2)$ = New features development by generator function

N = Selected features number

N_{Max} = Maximum selected features number

The automating data pre-processing can be executed through set of actions which have been chosen (O_S) from the default operating set (O_P) and implemented in the dataset. The selection of feature extraction is done through suitable feature selections (2N) from the dataset using recognition and even generate recent dependent pairs as (G (f1, f2)). The model selection as well as hyperparameter utilization through optimization in identifying the optimum parameter configuration from the infinite search area or learning from earlier designed models to the particular purposes. The stochastic learning approach, which has been utilized for many years to constrain the configuration space has been represented by the equation's final term.

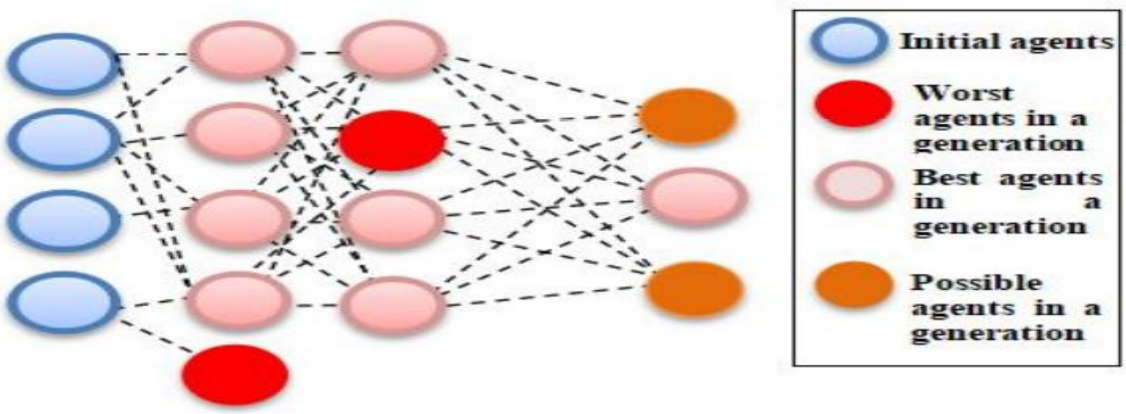

Figure 2 Working of evolutionary TPOT algorithm

The implementation of TPOT has been introduced with an advanced method in the process of optimization in adopting GP for identifying the optimal ML pipeline is illustrated in figure 2. In general, the construction of mathematical function in the tree have optimized based on fitness metrics like classification accuracy. Every tree generation has constructed through random mutation to the tree's structure or the operation that performs in each node of the tree. Iterating this process based on training generation amount that generates the optimum tree. Iteration process to the training generation number has produces an optimal tree. This can able to develop the optimized ML pipelines which assist in improving as well as surpassing the traditional supervised ML algorithm efficiently. Hence, the proposed TPOT is considered based on the classifier accuracy of each iterations. Selection, mutation and crossover operations have been utilized in improving the GP method for identifying the best pipeline. Thus, the research work involves in evaluating the TPOT efficiency with respect to selected hyperparameter for the prediction of adult learner interest and reliability of adult learner skills for further development. The overall architecture of TPOT model has been used in detecting the interest of adult learner in the centre is shown in figure 3.

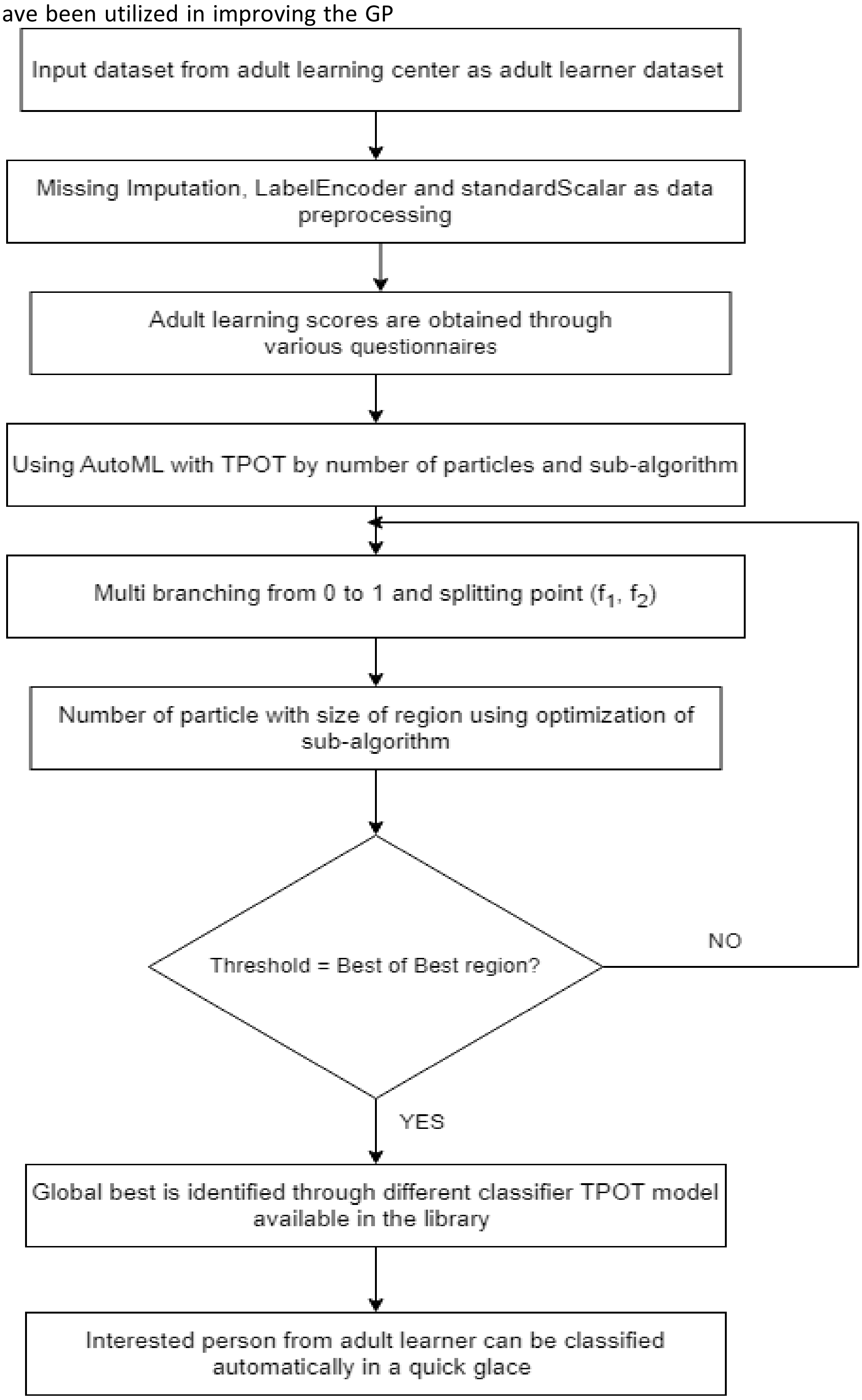

Figure 3 architecture of TPOT model to detect interest of adult learner

The computational tool that performs intelligent search through ML pipeline is TPOT which involves feature selection methods, supervised classification models, preprocessor and certain estimator or transformer which pursue the API of scikit-learn. There are various packages utilized in developing TPOT are NumPy, SciPy, update checker, scikit-learn, stopit, pandas, tqdm, xgboost and joblib. Moreover, the initially installed packages in python through pip install TPOT and installation need to be done before importing AutoML model. There are several combinations of pipeline extracted from TPOT that composed of data transformers available in the scikit-learn of python library like Min-Max Scaler, Max Abs Scaler, Normalizer, Standard Scaler (SS), polynomial features expansion and Binarizer, for preprocessor as well as Recursive Feature Elimination (RFE), Variance Threshold and Select Percentile (SP) for selectors. Hence, TPOT has provided various custom features like stacking estimator (SE), zero counts, a hot encoder, and wide sklearns transformer applications. Thus, the complete TPOT configuration contain 11 classifiers, 5 feature selectors and 14 feature transformers have connected with TPOT and made the best pipeline (best iteration) for any configurations.

Moreover, the TPOT time complexity is represented as $\partial(k)$

Where,

k = Tree depth or split count

When the sub algorithm is considered to be with time complexity as $\partial(1)$. The tree has developed with the depth k in all kind of targets like binary variable target and multivariable target. Assume that the sub-algorithm has been involved with time complexity $\partial(1)$ due to n iterations, the TPOT runs for $\partial(k)$ times.

Algorithm of TPOT

Input: Features as particles and iterations as sub-algorithm

Output: Best of iteration as global best

Step 1: Initialize the number of features as numbers of particles as Δ_1 and size of region as sub-algorithm as Δ_2

Step 2: When multi-branching from 1 to n and the splitting point $\in [f_1, f_2]$ else swapping the split on dimensions.

Step 3: Based on all region as number of particles as size of regions with optimization of sub-algorithm.

Step 4: If Better iteration is considered to be best of best regions is mentioned as Global best and set probability of region entering.

Step 5: Region with respect to probability $\cup$ $(0,1)$, remove the outer region from search space.

Step 6: If the threshold of the best region is not satisfied go to step 2 else Return the global best.

The TPOT pipeline generally begins using a number of duplicates of the complete dataset at the establishment of the tree structure as well as continues to employ feature selectors, function transformation, or the ML method, as shown in the example. The operators then modify the initial dataset and hand it off to the following operator in the tree. There are certain instances with hybrid operator creates a single dataset from several copies of the dataset.

Result And Discussion

The purpose of this proposed TPOT model with modified hidden layer is utilized for determining the interest present in the learner by selecting various tree-based optimizer. The purpose of the optimizer is to initiate the better learning rate as alpha =0.01 during training. Table 1 illustrates the various TPOT classifier model namely Stochastic Gradient Descent (SGD) classifier, Random Forest Tree (RFT) classifier, Decision Tree (DT) classifier and XGBoost classifier. The output layer with sigmoid has obtained with three different targets as low, medium and high. The low is represented as “0”, medium is represented as “1” and high is represented as “2”. The adult learner interest is measured through 6 different questionnaires as well as scores obtained in the test. From the given different TPOT models, SGD classifier has determined the best TPOT classifier model in recognizing the interest of adult learner. The current best Cross Validation (CV) is determined with best accuracy in which CV is defined as 5 as per this experimental research and the accuracy is shown in figure 4.

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Generation 1 - Current best internal CV score: 0.9185521885521885
Generation 2 - Current best internal CV score: 0.9185521885521885
Generation 3 - Current best internal CV score: 0.9357239057239057
Generation 4 - Current best internal CV score: 0.9357239057239057
Generation 5 - Current best internal CV score: 0.9357239057239057
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Figure 4 5fold CV score for SGD classifier method in TPOT model

The model accuracy is evaluated through confusion matrix class and its metrics in which the SGD classifier and RFT classifier is shown in figure 5 and figure 6. The value of classes in all TPOT MODEL classifier is illustrated in table 1.

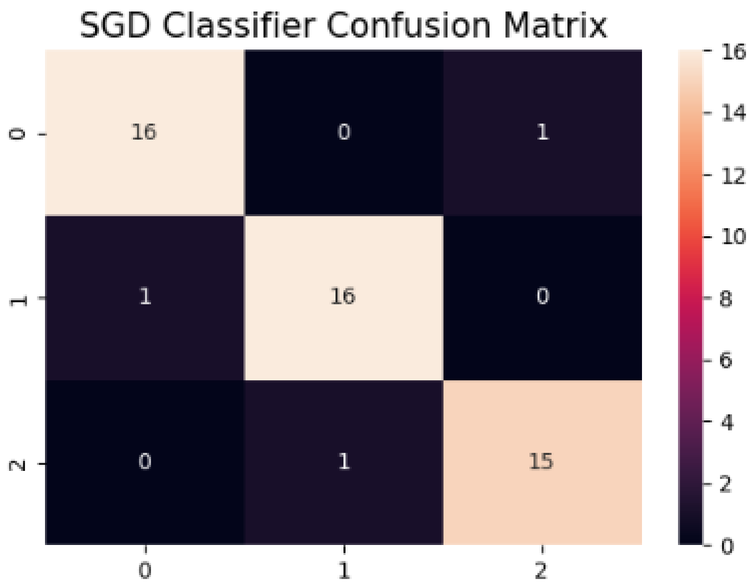

Figure 5 Confusion matrix of SGD classifier based on adult learner interest

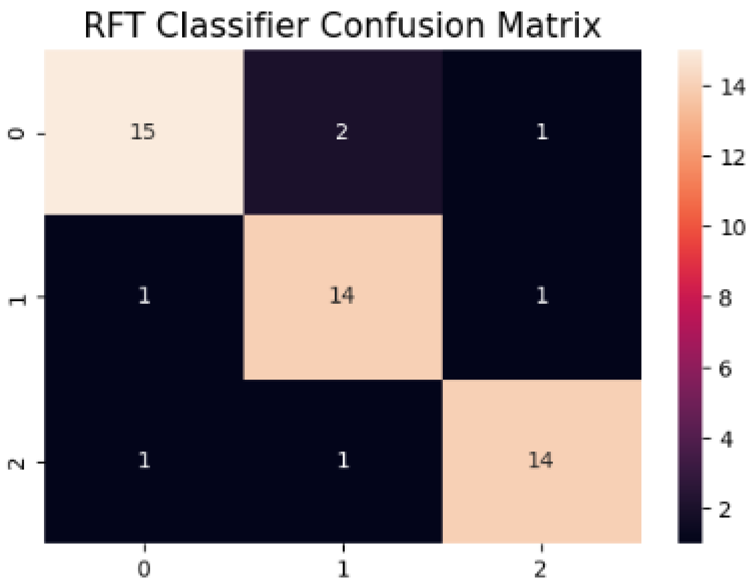

Figure 6 Confusion matrix of RFT classifier based on adult learner interest

Table 1 Confusion matric classes for adult learner interest

TPOT Classifier	Adult Learner Target Status	Confusion Matrix Classes for adult learner Interest			
		TP	TN	FP	FN
SGD Classifier	Low (0)	16	32	1	1
	Medium (1)	16	32	1	1
	High (2)	15	33	1	1
RFT Classifier	Low (0)	15	30	3	2
	Medium (1)	14	31	2	3
	High (2)	14	32	2	2
DT Classifier	Low (0)	14	31	3	2
	Medium (1)	16	29	2	3
	High (2)	13	33	2	2
XGBoost Classifier	Low (0)	15	32	2	1
	Medium (1)	16	31	1	2
	High (2)	15	33	1	1

Table 1 has illustrated the interest of adult learner for four different classifier of TPOT models in which 30% of testing sample is involved with 51 students as sample. Based on the samples, the target of interest can be assigned and evaluated through confusion matrix metrics such as accuracy, precision and recall.

Table 2 TPOT model with various classifier methods

Classification of TPOT model	Confusion matrix metrics					
	Micro Precision	Micro Recall	Micro F1-Score	Weighted Precision	Weighted Recall	Weighted F1-Score
SGD Classifier	94.0	94.0	94.0	94.0	94.0	94.0
RFT Classifier	86	86	86	86.32	86	86.01
DT Classifier	86	86	86	86.54	86	85.98
XGBoost Classifier	92	92	92	90.54	92	91.99

Table 2 illustrates the evaluation of TPOT model with 5 generation of cross validation and squared_hindge as loss parameter. The accuracy of multivariable classifier can be determined through micro precision, micro recall and micro F1-Score whereas SGD classifier has high accuracy as 94.0% while compare to other classifier of TPOT model.

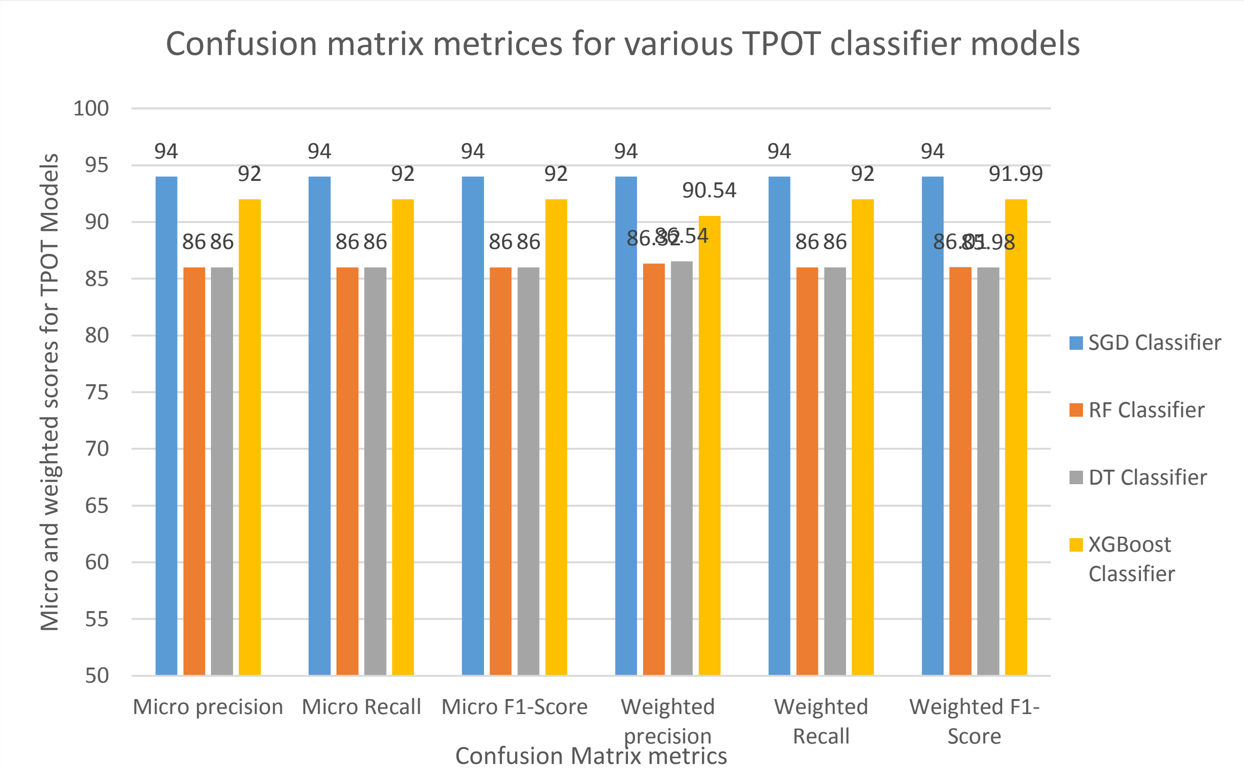

Figure 7 Micro and weighted value for various TPOT models

Figure 7 illustrates the micro and weighted value to four different TPOT models. The accuracy is said to be micro F1-Score for SGD is 94.0% which is comparatively higher than other TPOT model. The proposed TPOT model of SGD classifier has better prediction in classifying the interest of adult learner from the center of adult learner.

Figure 8 has illustrated the sensitivity and specificity of various TPOT models in which SGD classifier and XGBoost classifier has sensitivity as 0.938 and specificity as 0.971 which is higher than other TPOT models. Hence, it determines high true positive rate is better in both SGD classifier and XGBoost classifier in determine the interest of adult learner.

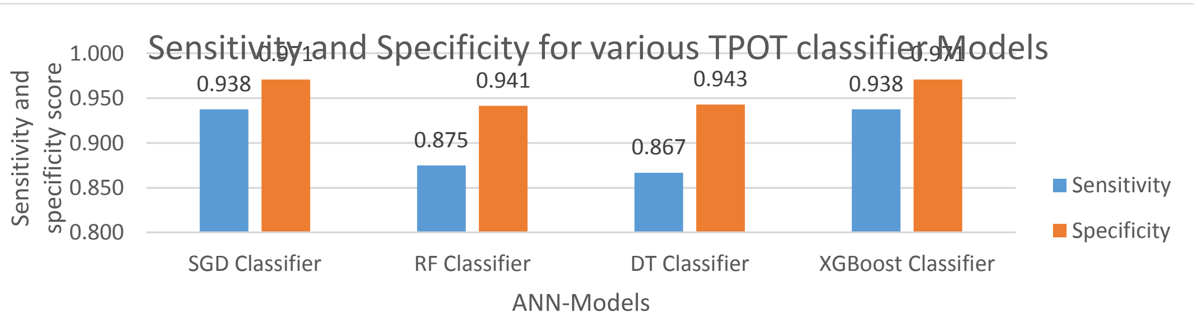

Figure 8 Sensitivity and specificity score for various TPOT models

Moreover, the sensitivity and specificity of several TPOT classifier model is same but the micro precision and micro recall is considered to be high in SGD classifier while comparing to XGBoost classifier. This is due to better learning rate with 5 cross validations in SGD classifier to understand the learner sample better than other TPOT classifier models.

Conclusion

The concept of development has accumulated the understanding of person's who passes through various stages in their lives and they have played an essential as well as different social and cultural roles and responsibilities. There is certain provision required to be considered in identifying the methods to recognize as well as respond for the set of practices and issues faced by the people who engages within their lives outside the classroom. Simultaneously, the facility required to understand the interest of the adult learner and development practices and applying pressure to the learner to meet the staff expectation about suitable model of teaching and behavior to the adult learner to improve the interest in learn more and spent the time valuable. Hence, the proposed TPOT model with SGD classifier has better learning rate with 5-cross validation obtain better accuracy as 94.0% while compared to other TPOT models. The selection of TPOT model is suggested due to selection of maximum number of feature selection for better understanding of model. This TPOT model with SGD classifier is essential in resisting more pressure on non-interested learner for further development of skills. Instead, the learner is made to focus on basic study to bring their interest through modifying the mode of teaching to the adult learner.

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