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Construction of a comprehensive measurement model for financial talent training quality under the OBE concept

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ABSTRACT

The rapid evolution of the socio-economic landscape and the progressive depth of higher education have catalyzed the emergence of Outcome-Based Education (OBE) in nurturing financial expertise. This studies is dedicated to the formulation of an exhaustive evaluative framework for the high-quality guarantee of economic brain development in the OBE paradigm. Our objective is to holistically appraise student development across the spectra of information acquisition, talent enhancement, and ordinary literacy. To this give up, we combine multidisciplinary insights, incorporating a okay-capability multi-dimensional evaluation version, real-global challenge-based totally evaluation strategies, and a machine of persistent feedback and iterative refinement. This integration ensures both the medical rigor and the realistic relevance of our schooling approach. In the end, this version endeavors to supply a more based and efficacious pedagogical route for the fostering of economic acumen, thereby equipping students to greater efficiently navigate the challenges inherent of their destiny expert trajectories.

Keywords: OBE, economic brain education, comprehensive first-rate size version, Multi-dimensional assessment, actual venture driven, ok-ability

1. Introduction

In cutting-edge rapidly evolving social and monetary panorama, the goal of higher schooling [1-3] extends past offering understanding to nurturing people with well-rounded literacy and practical software competencies. To achieve this objective, the thinking of OBE [4-6] has emerged as an influential schooling model globally, specially in the financial sector [7-9].

OBE underscores the cultivation of exact and observable consequences that scholars can acquire by means of the end result of their research, moving the focal point from mere path coverage to a student-centric approach of beginners that specialize in what is found out instead of instructors specializing in what's taught. In better training, OBE now not solely concentrates on imparting

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situation know-how but also emphasizes college students' potential to apply this knowledge to deal with challenges in professional fields, together with their holistic aptitude in instructional and expert domains.

As an necessary factor of higher training, the nature and specificity of finance and economics majors necessitate the development of experts adept at both perception and elegantly making use of concept. The utility of OBE in the training of monetary skills holds sizeable history and importance.

Conventional monetary education [10-11] frequently fixates excessively at the infusion of theoretical know-how. In assessment, OBE advocates for college kids to recognise and follow received knowledge through realistic operations and undertaking practices, fostering adaptability to future career challenges.

The economic discipline imposes stringent necessities on professional characteristics, which includes conversation abilities [12], teamwork abilities [13], and trouble-solving skills [14-15]. With the aid of emphasizing the accumulation of sensible paintings revel in, OBE aids in cultivating college students' professional traits, higher preparing them for the demands of the workplace.

The utility of OBE aligns finance principal schooling extra intently with actual expert needs. Via specific studying targets and outcomes, academic establishments can adapt route services according to industry trends and needs, making sure that graduates own the skills and skills demanded through the marketplace.

Within the schooling of financial abilities, the application of OBE isn't always merely an schooling version [16-17], however also a proactive reaction to the evolution of better education. Specially, the significance of OBE inside the training of financial abilities manifests in strengthening practical capacity [18], selling interdisciplinary integration [19-20], improving comprehensive great [21], and adapting to enterprise modifications [22].

OBE engages finance and economics college students in tasks, practical physical games, and simulated eventualities, improving their ability to address real-global problems.

Ffinancial abilities collaborate with professionals from numerous fields of their careers. OBE breaks down disciplinary limitations, fostering interdisciplinary integration and cultivating economic experts with complete characteristics.

At the same time as traditional financial education emphasizes professional understanding, OBE prioritizes college students' ordinary first-class, consisting of conversation competencies, innovation, and teamwork. This results in more well-rounded financial professionals.

Given the rapid technological and market changes in the financial sector, OBE enables students to better acclimate to these shifts. Participation in actual projects facilitates a deeper understanding and quicker adaptation to industry trends.

In the subsequent sections of the paper, we will delve into constructing a comprehensive measurement model for evaluating the training quality of financial talents based on the OBE concept. This endeavor aims to comprehensively assess students' academic achievements and training quality in the field, representing not only a further exploration of the OBE concept but also an innovative enhancement of the financial talent training model.

2. Related Works

In the realm of evaluating the quality of financial talent training [23-24] and exploring the application of the OBE concept, we have uncovered a plethora of pertinent documents that offer valuable insights and inspiration for integrating the OBE concept within the financial sector. This article aims to review existing research on the quality assessment of financial talent training, delineate the distinctions brought about by the OBE concept in this context, and extract applicable models from the experiences of diverse disciplines.

The cultivation of financial and economic talents stands as a perennial concern in higher education.Pupils are nowadays devoted to enhancing students' standard abilities and aligning them with market demands. Traditional evaluation methods in assessing the exceptional of monetary Genius training predominantly deal with subject understanding [25-26], regularly neglecting the development of students' sensible utility capabilities and comprehensive literacy in actual-world scenarios. Consequently, the mixing of the OBE notion on this area emerges as a vital reform path.

OBE locations a sturdy emphasis on college students' getting to know consequences and sensible software skills, representing a splendid departure from the conventional curriculum-centric instructional paradigm. Inside the context of financial brain training, the disparities introduced through OBE are especially obvious within the following facets. First of all, there's a clean articulation of studying goals. OBE necessitates exactly defining the desires and consequences that scholars ought to obtain at some point of the schooling manner, transferring the focus from the mere content material of guides to cultivating realistic software and problem-solving competencies in monetary abilities. Secondly, there is a heightened emphasis on realistic work revel in [27-29]. OBE underscores the importance of college students' realistic publicity, encompassing internships, projects, and real-world gaining knowledge of studies. Within the subject of finance and economics, this involves lively participation in practical activities which include simulated markets and actual investment tasks to decorate adaptability to professional environments. Finally, OBE promotes the improvement of complete features. This encompasses verbal exchange skills, teamwork, innovation, and other components, contrasting with traditional economic schooling's essential emphasis on offering professional information.

In diverse concern regions, OBE has done outstanding success, supplying constructive stories that can be leveraged as references for constructing a comprehensive measurement version for comparing the pleasant of economic brain schooling. Regarding multidimensional evaluation fashions [30-32], numerous disciplines have embraced such fashions under OBE, covering numerous aspects such as understanding, competencies, and attitudes. This serves as a guide for growing a comprehensive size version within the field of finance and economics, permitting the holistic assessment of college students' development at specific ranges. In phrases of venture-driven assessment, some disciplines make use of task-driven assessment methods to gauge students' sensible capabilities thru tangible projects. Inside the context of economic intelligence education, those experiences can inform the incorporation of more actual investment tasks and simulated marketplace activities. Regarding remarks and improvement mechanisms [33], OBE advocates for continuous assessment and enhancement to recognise academic dreams. In finance and economics, insights from other disciplines can manual the establishment of an effective feedback and improvement mechanism, aligning educational practices with enterprise wishes and pupil improvement.

This literature evaluate delves into the present day country of fine evaluation in financial brain training, underscoring the exclusive functions of the OBE idea in this context. Precious reviews drawn from other disciplines provide insightful suggestion for building a complete dimension model for the fine of financial intelligence schooling. Moving forward, the next step involves constructing a more scientific and practical comprehensive measurement model based on these experiences to robustly support the advancement of higher financial education.

3. Method

3.1. Denoising method

Use the sample division strategy to compare the sample loss value and the noise value to filter out the noise samples.

The sample division strategy based on a fixed threshold first sets a threshold to filter the original sound samples, then uses formula (1) to calculate the loss value of x_i, and filters out the noise samples according to the size of the loss value. However, if it is too large or too small The fixed threshold value will cause the network to produce erroneous sample divisions, thereby reducing the classification accuracy of the network.

$$L_E = -\sum_i y_i \log f\left(x_i;\vartheta\right) + \left(1-y_i\right)\log\left(1-f\left(x_i;\vartheta\right)\right) \tag{1}$$

where $f\left(x_i;\vartheta\right)$ represents the network's predicted value for sample x_i

In order to solve the problem of misclassification caused by fixed values, some scholars have proposed a dynamic threshold division strategy. This strategy uses the regularization loss L_R in equation (2) to improve the network's confidence in clean samples, and then adjusts it through equation (3) The original acoustic value $\alpha_{i,t}$ of the current round t , and calculate the overall loss value L of the current sample according to Equation (4), and finally compare the loss value with the current noise value according to Equation (5), and filter out samples that are greater than the audible value. As noise samples

$$L_R\left(x_i\right) = -\beta \cdot EL_E \tag{2}$$

$$\alpha_{i,t} = \frac{1}{N}\sum L_E^{(t)} + L_R\left(x_i\right) \tag{3}$$

$$L = L_E^{(t)} + L_R\left(x_i\right) \tag{4}$$

$$v = 1\left(L < \alpha_{i,t}\right) \tag{5}$$

Among them, β is the weight factor of sample loss, $1(\cdot)$ is the indicator function, when $v_i^{(t)} = 0$, it means that sample i is a noise sample, and when $v_i^{(t)} = 1$, it means that sample i is a clean sample.

Digital augmentation enriches the diversity of samples by adding weak label perturbations to samples or generating new samples. Traditional digital augmentation includes image translation, conversion, color transformation, etc. Some scholars have proposed a mixup algorithm, which linearly enhances any two samples $\left(x_i, y_i\right)$ and $\left(x_j, y_j\right)$ based on formula (6) and formula (7) to generate a new sample $\left(x', y'\right)$.

$$x' = \lambda x_i + (1-\lambda)x_j \tag{6}$$

$$y' = \lambda y_i + (1-\lambda)y_j \tag{7}$$

Among them, λ is used to control the proportion of data enhancement.

However, the mixup algorithm is prone to generate new noise samples in the process of adding training samples, thereby misleading the network to learn wrong sample information. In order to reduce the interference of original sounds in new samples, some scholars have proposed a spatial enhancement algorithm, which combines the characteristics of the samples. To perform feature enhancement, firstly extract the first-order features u_i and u_j of x_i and x_j and the second-order features σ_i and σ_j according to equations (8) and (9) respectively, and then compare the feature distance of The characteristic moments of x_j are fused to achieve a combination of characteristic moments, thereby assisting the network in learning the combined features of new samples.

$$u = \frac{1}{N}\sum_N x \tag{8}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_N (x-u)^2 + \varepsilon} \tag{9}$$

$$x_i^{(j)} = \sigma_j \frac{x_i - u_i}{\sigma_i} + u_j \tag{10}$$

Among them, E is a constant, and $x_i^{(j)}$ is the generated sample combination feature.

3.2. K-Means algorithm

The K-Means algorithm is a classical clustering technique employed to partition a dataset into K distinct groups (clusters), with each data point assigned to the cluster whose center is nearest. This iterative algorithm refines the cluster centers until a convergence criterion is satisfied, aiming to minimize the sum of squared distances between each data point and the center of its assigned cluster. Figure 1 illustrates the step-by-step flow of the algorithm.

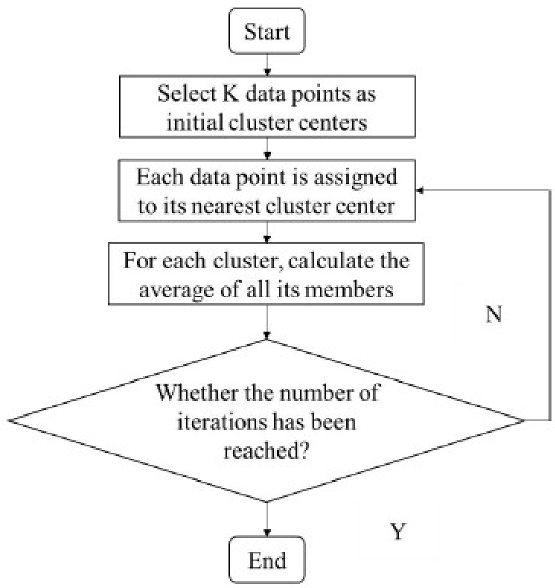

Fig. 1. Algorithm flowchart

Cluster Center Update Formula

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x \tag{11}$$

where, μ_i represents the center of cluster C_i, $|C_i|$ is the number of data points in cluster C_i, and x is a data point in cluster C_i.

Squared Distance Formula from Data Point to Cluster Center

$$D(x, \mu_i)^2 = \sum_{j=1}^{n} \left(x_j - \mu_{i_j}\right)^2 \tag{12}$$

Here, $D(x, \mu_i)$ denotes the squared distance from data point x to cluster center μ_i, n is the dimensionality of the data point, x_j and μ_{i_j} represent the coordinates of data point x and cluster center μ_i in the j-th dimension, respectively.

Objective Function

$$J = \sum_{i=1}^{K} \sum_{x \in C_i} D\left(x_j - \mu_{i_j}\right)^2 \tag{13}$$

The goal of the K-Means algorithm is to minimize the above objective function J. This is achieved through iterative optimization of cluster centers to minimize the sum of squared distances within clusters.

3.3. Dataset introduction

Table 1. The pseudocode of the **K-means**

Algorithm 1: K-means clustering
Input: data set D, number of clusters K
Output: clustering results
1: Select K data points as initial clustering centers
2: Repeat the following steps until the cluster center no longer changes:
3: Assign each point to the nearest cluster center to form K clusters
4: For each cluster, recalculate the cluster center (i.e. calculate the mean of all points in the cluster)
5: Return clustering results and cluster centers

We have systematically organized the gathered information and termed this compilation the Financial Talent Training Quality Comprehensive Measurement Dataset (FETQM Dataset). The dataset encompasses approximately 10,000 samples, each characterized by an extensive set of over 50 features. These features encompass diverse aspects such as student attributes, course details, teacher characteristics, and employment status, among others. Figure 2 illustrates the distribution of these features within the dataset. The collection of data stems from numerous higher education institutions specializing in finance and economics, ensuring a wide-reaching and inclusive representation ofinformation. The datasetis distinguished by its broad coverage, high representativeness, and practical applicability.

Table 1presents the pseudo code ofthe K-means algorithm utilized in our analysis.

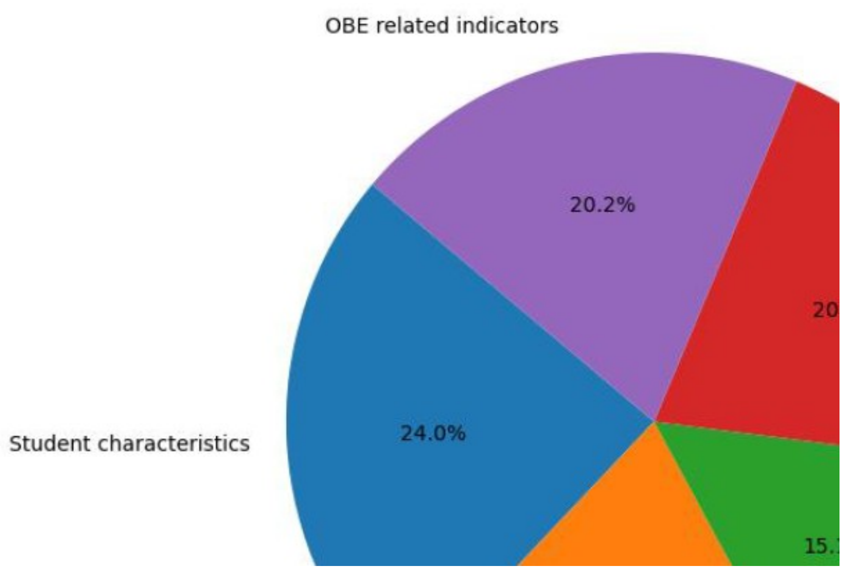

Fig. 2. Data set proportion

4. Experiment Results

4.1. Public data set testing

Firstly, we evaluate the K-means algorithm using a publicly available handwritten dataset. Figure 3 illustrates a comparison ofalgorithmic accuracy, loss, and running time.

Figure 3 offers a complete visualization of algorithm overall performance, incorporating 3 key metrics accuracy, loss price, and jogging time. The discern makes use of 2 awesome graphs to bring the records, employing a bar chart to depict accuracy and loss values, at the same time as a line chart represents running time. The Y-axis ofevery sketch corresponds to a wonderful metric, with the Y-axis of the bar chart denoting percent and loss value, and the Y-axis ofthe line chart denoting time in seconds.

Within the bar chart segment, the peak of the accuracy bar indicates the algorithm's predictive accuracy, that is suggested as 95.88%. This high accuracy rate shows the set of rules's functionality to make accurate predictions with a sizable stage of reliability. The accuracy bar, depicted in blue and located on the left, dominates the chart, underscoring the pivotal function of accuracy in comparing set ofrules performance.

Loss fee, another essential performance metric, indicates the disparity among the set of rules's expected results and the real values. In this illustration, the loss price is portrayed in red, with a top of 0.042, a fairly small value in comparison to the accuracy bar. In the course of version optimization, minimizing the loss price is paramount, as smaller values mean nearer alignment between the version's predictions and actual effects, signifying more suitable performance.

The walking time is illustrated by means ofgreen dots and lines, with a selected fee of5.4 seconds. Going for walks time serves as an immediate indicator of set of rules performance, reflecting the period required for the algorithm to manner facts. In sensible packages, a shorter running time suggests the algorithm's suitability for scenarios necessitating swift responses, together with real-time facts processing and on-line decision support.

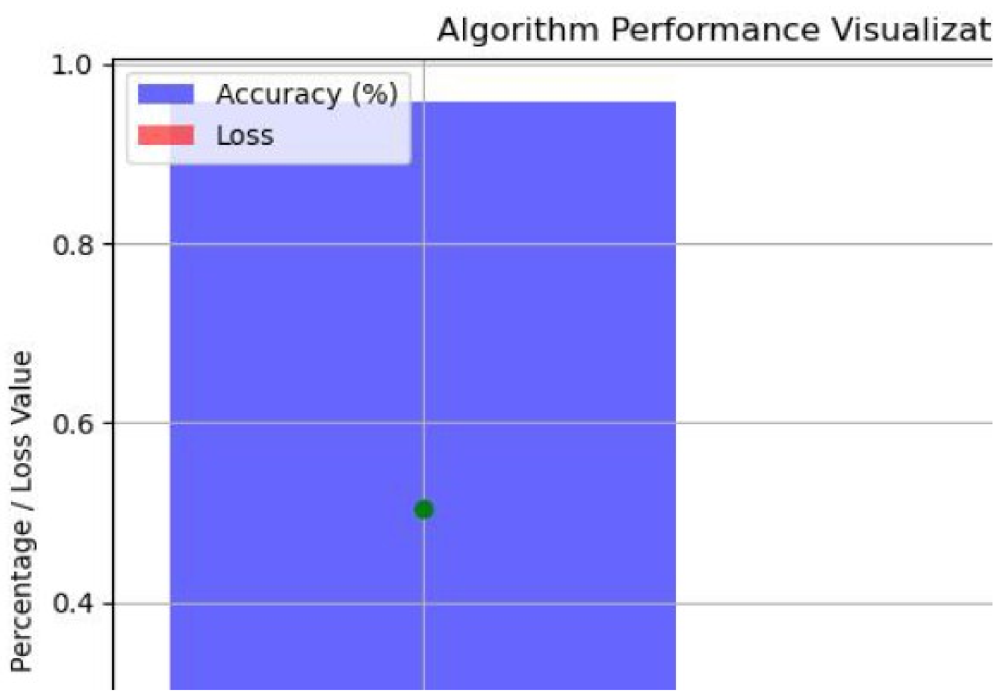

Fig. 3. Algorithm accuracy and loss and running time

4.2. Result

Next, we are able to behavior assessments at the dataset accrued in this article and examine the results of the k-capacity set of rules with the help Vector Machines (SVM) set of rules. Figure 4 illustrates the accuracy overall performance of the 2 device learning algorithms, k-capability and SVM, across extraordinary numbers of iterations. Accuracy, a indispensable metric for assessing model performance, reflects the version's precision in predictions. Reading this dataset approves us to draw important observations and conclusions.

First off, it is obtrusive from the statistics that the accuracy steadily improves with an growth in the variety of iterations for both algorithms. This indicates the effectiveness of new release in enhancing version overall performance. Within the okay-potential algorithm, the accuracy improved extensively from 60.51% to 84.62% because the number of iterations stepped forward from 10 to one hundred. Further, in the SVM set of rules, the accuracy rose from 58.82% to 81.29% over the equal iteration variety.

Secondly, at each new release, the okay-potential set of rules demonstrates higher accuracy than the SVM algorithm. This discrepancy may be attributed to the reality that the k-ability set of rules is an unmonitored gaining knowledge of method designed for clustering data, even as SVM is a supervised studying set of rules used for information classification. Ok-means excels in clustering information, main to superior overall performance in this challenge. But, the SVM algorithm's accuracy also gradually improves, indicating ongoing version optimization at some stage in the iterative method.

Furthermore, the accuracy of the k-capacity set of rules begins to stabilize after the quantity of iterations exceeds 50, even as the SVM set of rules stabilizes after surpassing eighty iterations. This suggests that further growing the variety of iterations might not appreciably decorate the model's accuracy however ought to improve computational fees.

In end, this dataset highlights the prevalence of ok-capability over the SVM algorithm in terms of accuracy because the range of iterations increases.

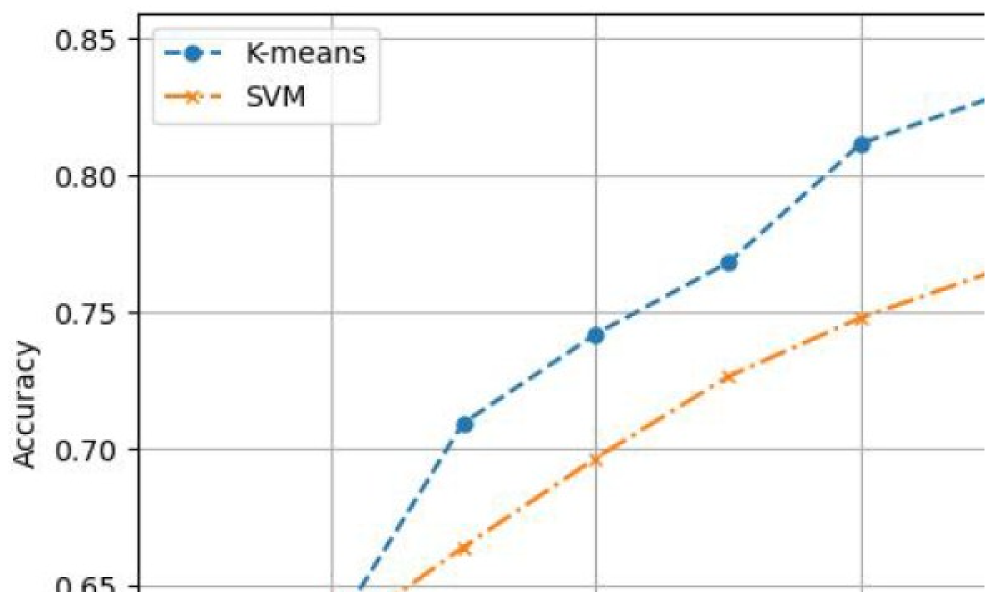

Fig. 4. Accuracy changes with the number of iterations

As illustrated in Figure 5, the depictedboxplotserves as a comparative analysis toolfor evaluating the performance oftwo distinct machine learning methods K-means and SVM. The focus here is on the metric of Recall as a performance indicator. A box plot is a statistical graphic designed to elucidate data distribution, encompassing medians, quartiles, and outliers.

In the graphical representation, Recall values for both methods predominantly cluster between 0.7 and 1.0. Notably, the median Recall of K-means appears marginally lower than that of SVM. Simultaneously, the box for K-means appears slightly shorter, implying a narrower distribution range of Recall values and, consequently, a relatively more stable performance. Conversely, the SVM's box exhibits greater length, indicative of increased variability in Recall values. Comparable whisker lengths endorse that facts points for both algorithms are disbursed over a similar variety. No discernible outliers are marked, asserting that all Recall values fall in the everyday range.

Several preliminary inferences may be drawn from the container plot. First of all, the higher median Recall of the SVM algorithm implies advanced average performance as compared to ok-potential on this specific metric. Secondly, okay-skill famous extra consistency in Recall performance, attributed to its smaller interquartile range. Lastly, the truth that Recall values for each algorithms remain within the discovered variety indicates the absence of severe overall performance outliers in this dataset.

It is important to renowned that container plots provide a visible illustration in preference to an exhaustive statistical analysis. To derive more unique conclusions, similarly statistical checks, together with suggest calculation, general deviation analysis, and speculation testing, are vital for a complete grasp of overall performance disparities among the 2 algorithms.

In summary, this box plot gives an intuitive evaluation, illustrating the distribution of performance for k-skill and SVM system gaining knowledge of algorithms whilst utilizing Recall because the evaluation criterion on a selected dataset.

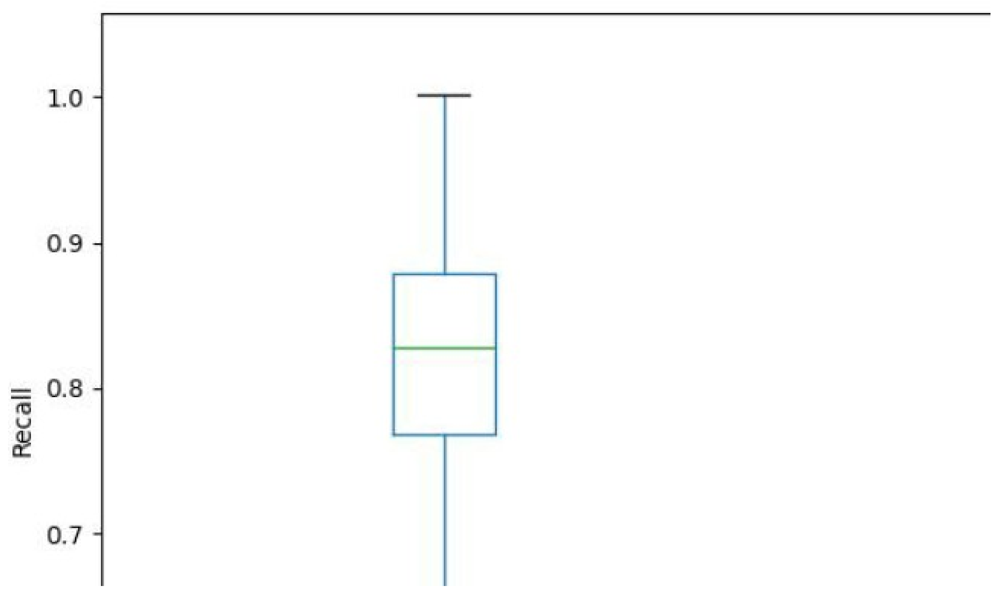

Fig. 5. Comparison of Recall

The generated plot is a aspect-by using-aspect histogram comparing the processing instances of two gadget gaining knowledge of algorithms k-capacity and SVM. Every histogram represents the distribution of processing instances over a hundred iterations, assuming a regular distribution with specific ability and standard deviations.

The ok-ability set of rules's processing times are focused around 47 seconds with a popular deviation of 3, whilst the SVM's instances are centered around 52 seconds with a barely smaller fashionable deviation of 2.8. The histogram for okay-capacity is barely to the left of the SVM histogram, indicating that, on average, k-potential processed the facts quicker than SVM.

Both histograms are plotted with a bin size of 20 and have semi-transparent bars (alpha set to 0.5) so that overlapping areas can be visualized. The K-means histogram is colored differently from the SVM histogram to distinguish between the two. Overlapping areas where both histograms are visible suggest a range of processing times where both algorithms have common values.

The use of'Times New Roman' font for the plot's text was intended, but it appears that the font was not found and thus, a fallback font was used instead. The overall layout is tight, meaning there is minimal whitespace around the plot, making the histogram the central focus of Figure 6.

Normal, this plot is a visual representation that allows for a quick contrast of the processing time overall performance between the two algorithms. It shows that even as there is a few overlap, okay-capability tends to have a quicker processing time than SVM given the information generated. The distribution of processing times for k-potential is also slightly more unfold out, indicating a bit extra variability in processing time throughout iterations in comparison to SVM.

The histograms offer perception into the efficiency of the algorithms beneath the given situations. Customers can infer no longer only the average processing time however also the consistency of each set of rules's overall performance. For a more specified evaluation, one would possibly reflect on consideration on statistical tests or summary records like the imply and median processing instances, which aren't explicitly proven within the histogram. The plot is a common way to visually evaluate 2 distributions and may function a initial step in overall performance evaluation earlier than carrying out more in-intensity evaluation.

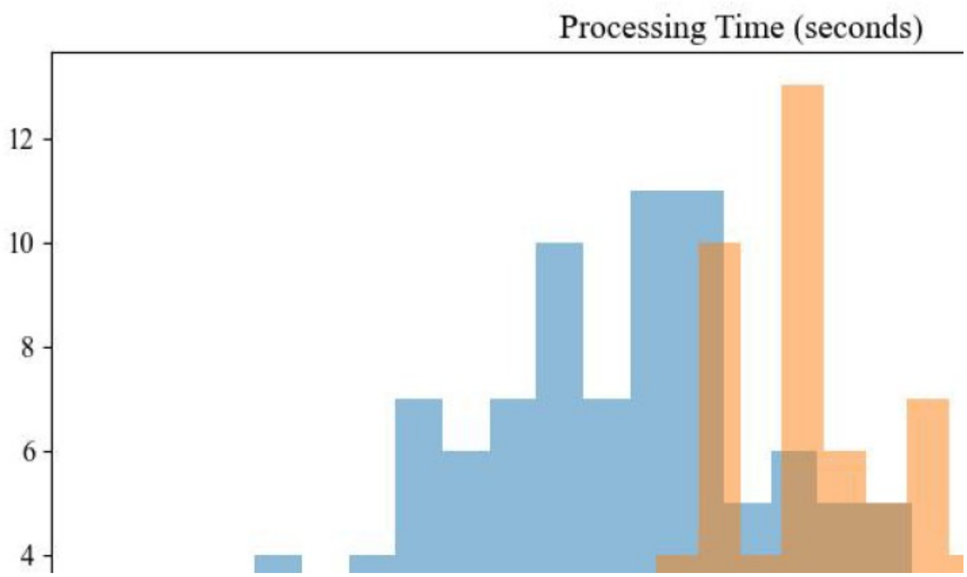

Fig. 6. Comparison curves of F1 Score

5. Conclusion and Discussion

The effects of our model show that a focal point on learning outcomes permits a more specific quantification and enhancement of the nice of finance publications. As an instance, the version identifies the most powerful teaching methods and areas wanting development by way of comparing college students' mastery of key monetary concepts and abilities. This analytical technique aligns at once with the OBE notion, emphasizing that the instructional process need to revolve around college students' very last learning achievements.

Our model has undergone testing across various educational establishments, which include universities, vocational schools, and on-line courses. It considers numerous academic situations which includes college, direction assets, and student backgrounds. Notably, the model reveals a high diploma of adaptability, taking into consideration parameter changes to suit different coaching environments and scholar populations. This adaptability is fundamental throughout OBE implementation, empowering educators to customize and optimize teaching strategies based on specific situations.

Studies findings suggest that measurement models offer treasured insights for policymakers and educators to decorate training coverage and curriculum layout. The data-pushed nature of the version unveils key elements contributing to college students' educational achievement, guiding the rational allocation of instructional sources and the innovation of teaching methods. Furthermore, the version underscores the development of lifelong learning skills, specifically vital for finance and economics students, given the swiftly changing financial landscape requiring continuous knowledge and talent updates.

The look at underscores how a comprehensive dimension version, rooted in the OBE thinking, can enhance the excellent of financial talent training. The version no longer only assesses college students' information and ability stages however also evaluates necessary idea, hassle-solving, and decision-making capabilities - vital competencies for future economic experts.

While our model provides valuable insights, it is not without limitations. For example, further field validation may be necessary to confirm its generalizability across diverse countries and cultural contexts. Future research could explore the integration of these factors into the model and refine it to accommodate online and blended learning environments.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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