Title Page:

Improved accuracy in real time object measurement using Novel support vector machine in comparison with SSD (Single Shot Multi box Detector) algorithm.

Student name[1] , Dr.guide name[2]

Student Name[1] :Burle Damodar
Research Scholar,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
student mail id: damodarb4203.sse@saveetha.com

Dr.Guide name[2],
Project Guide, Corresponding Author,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
jagadeeshp@saveetha.com

Abstract:

Aim: To implement a real time object measurement in images using Novel support vector machine(SVM) in comparison with Single Shot Multi box Detector algorithm(SSD) in order to more accurately predict Performance Evaluation. **Materials and Methods:** In this study, two groups are involved are the Novel support vector machine(SVM) (N=20) and the Single Shot Multi box Detector algorithm(SSD) (N=20) are applied to the dataset the percentage of valid predictions relative to ground truth that indicates how well the SVM algorithm predicted the object's dimensions based on a calculation akin to SVM accuracy, the accuracy of the SSD algorithm in estimating the dimensions of the object for enhancing the accuracy using a G power value of 0.8 and $\alpha = 0.05$ and the sample size for each group is 9. Accuracy is the primary criterion used to assess real-time object measuring performance in photographs. **Outcome:** The Single Shot Multi box Detector (SSD) technique achieves an accuracy of 75.5%, while the real-time object measurement system using the Novel support vector machine (SVM) algorithm achieves 91.1% measurement accuracy. Based on an independent sample t-test ($p<0.05$), this shows a statistically significant difference in the performance of both algorithms, with a p-value of 0.023. **Result:** The object measurement accuracy of the real-time system is higher than that of the Single Shot multi box Detector (SSD) technique while using the Novel support vector machine (SVM) algorithm.

Keywords: Accuracy, machine learning, single shot multi box detector (SSD), images , Novel support vector machine (SVM), and real-time object measurement.

Introduction:

Real-time object measurement(Jain 2012) in photos is a crucial enabler of progress in many different disciplines, not just an innovation in technology. This initiative seeks to develop real-time object measurement using creative ideas and methods, acknowledging the revolutionary potential of such capabilities.This project's main goal is to create reliable algorithms and systems that can precisely identify, quantify, and analyze objects in photos in real time. (Sri Sairam College of Engineering 2022) By utilizing state-of-the-art techniques in deep learning, machine learning, and computer vision, the project aims to push the limits of what is possible in terms of scalability, speed, and accuracy.Addressing the current issues related to real-time object measuring is one of the main goals of this project. Measurement of object size and distance is becoming increasingly and more important in various applications, particularly in mobile autonomous. (Jiang et al. 2023) Recent years have seen notable progress in the study of object distance measuring from photographs, with a number of methods being put forth to provide precise and instantaneous measurements.

As both Google Scholar (25,800) and Science Direct (90,193) reveal, a substantial number of closely related articles published over the last five years highlight the increasing interest and research effort in the topic of real-time object measurement in pictures. The rising significance of developing techniques and technology for precise and effective object measurement in dynamic situations is reflected in this spike in scholarly production. The 25,800 closely related publications found on Google Scholar point to a strong research ecosystem centered on real-time object measurement in photos. (Shen et al. 2023) This platform functions as an all-inclusive library of academic literature, covering a broad spectrum of subjects and approaches associated with object measurement. Given that the majority of autonomous systems in use today have vision sensors or cameras, it is advantageous to use the vision data to gather size and distance information that can help the system. (Sisodia et al. 2023) A monocular vision system using Hough transformations and relative object size to calculate distance was proposed by (Dziech and Czyzewski 2012). A camera and a revolving mirror are used in distance measurement method, which analyzes reflected image sequences to calculate distance based on pixel motion.Increased attention has been paid in recent years to the use of several vision sensors—especially those in stereo configurations—to improve the accuracy of object size and distance measurements. Used differences between images taken by stereo cameras to evaluate safe driving distances using stereo vision and colleagues enhanced disparity computations to attain more precise distance estimations across a broader field of view. Real-time object measurement in photos has great promise in a variety of industries, providing creative solutions and improving different procedures. Applications of this technology are significant in the areas of quality control and industrial automation. Real-time measuring in industrial environments maximizes efficiency and reduces faults by guaranteeing that goods fit exact dimensions standards. For example, vital elements like engine parts or chassis frames can be precisely measured in real-time in the automotive production industry to guarantee they meet tight tolerances and preserve product quality(Streit, Angle, and Efe 2020).

We hope to shed light on the advantages and disadvantages of SSD and SVM algorithms for real-time object measurement in images through this comparative research. We are able to decide which algorithms are appropriate for a certain application by knowing their performance characteristics. The ultimate objective is to improve real-time object measuring accuracy and precision, expanding the capabilities of systems used in dynamic situations.There are clear benefits and trade-offs between SVM and SSD for real-time object measuring in images(Hunter and Harold 1987). SVM is superior in terms of accuracy and precision, but SSD outperforms in terms of detection speed and ease of training. As a result, the particular needs of the application determine which of SVM and SSD to use. SVM may be favored for activities where accuracy and precision are of the utmost importance, whereas SSD is the best choice for applications that require quick and effective real-time object detection. Ultimately, choosing the best method for real-time object measurement in photos requires an awareness of the advantages and disadvantages of each algorithm(Donaldson et al. 2015).

MATERIALS AND METHODS

The investigation was carried out in the Computer Science and Engineering Department's Software Laboratory at Saveetha University. The Real time object measurement dataset collected from kaggle (https://www.kaggle.com/code/aruchomu/yolo-v3-object-detection-in-tensorflow) which consists of images of different categories. The database is structured so that 75% of it is dedicated to training, and 25% is for testing. There are two sets taken, and each set has ten data samples; the total number of samples taken into consideration is twenty. Group 1 was a Novel support vector machine(SVM) algorithm and Group 2 was a Single Short Multi box Detector(SSD) algorithm. Python with openCv software is used for the implementation. The sample size was determined by using previous research from (Stereo Vision Images Processing for Real-time Object Distance and Size Measurements, 2012) at google scholar. The threshold for the calculation was set at 0.05, the G power was set at 80%, and the confidence interval was set at 95%.

Windows 11 OS served as the machine learning platform for the proposed work, which was developed and implemented using Python OpenCV software. The hardware setup included a 16 GB RAM and an Intel Core i5 processor. It was a 64-bit system. The code was implemented using the Python programming language. The dataset is being worked on behind the scenes during code execution in order to finish an output process for accuracy. The following are independent variables: images, detection, object, measurement, classification points. Accuracy is a dependent variable. In order to increase accuracy, the analysis is based on both independent and dependent variables.

Novel support vector machine(SVM)

A supervised machine learning approach called Novel support vector machine (SVM) is used for regression as well as classification. Even yet, classification problems are the most appropriate use for regression problems. The SVM algorithm's primary goal is to locate the best hyperplane in an N-dimensional space that may be used to divide data points into various feature space classes. The hyperplane attempts to maintain the largest possible buffer between the nearest points of various classes. The number of features determines the hyperplane's dimension. The hyperplane is essentially a line if there are just two input features. The hyperplane transforms into a 2-D plane if there are three input features. It gets harder to envision when the number of features exceeds three.

$\sum n = 1 \; N (\alpha n - \alpha n *) = 0 \;\; \forall \; n : 0 \leq \alpha n \leq C \;\; \forall \; n : 0 \leq \alpha n * \leq C \; . \; \beta = \sum n = 1 \; N (\alpha n - \alpha n *) \; x n \; .$

Only the support vectors are necessary for the function that predicts new values to work: $f (x) = \sum n = 1 \; N (\alpha n - \alpha n *) (x n ' x) + b$.

Algorithm

Input: Image dataset

Output: Measurement of real time objects in images

Function SVM(data, test_instance, k)

Step 1. Adjust the regularization parameter \(C\) and the kernel type as hyperparameters.

Step 2. Start lists at the beginning so that each iteration records accuracy as well as loss of validation and training.

Step 3. Preprocess the data by performing feature scaling and dividing it into training and validation sets.

Step 4. Use the chosen kernel function (such as a linear, polynomial, or radial basis function) to initialize the SVM model.

Step 5. Use training data to train the SVM model, updating parameters and minimizing the loss function.

Step 6. Use validation data to assess the trained SVM model's performance.

Step 7. Modify kernel parameters and \(C\) to optimize hyperparameters based on validation performance.

Step 8. Refine the model as needed by going through steps 5-7 again and experimenting with different regularization or optimisation strategies.

Step 9: Use the test set to evaluate the finished SVM model and gauge its generalization performance.

Step 10: Plot the accuracy and loss curves for training and validation, and display the results to demonstrate how the model is learning.

Step 11: To find out more about the SVM model's prediction process, analyze the model and look at the learned decision boundary and support vectors.

Step 12: Monitoring and Deployment: This step involves introducing the trained SVM model into production or real-world settings.

Single Shot Multibox Detector(SSD)

With SSD, we only need to force us to take one shot in order to identify multiple objects within the image, while RPN-based approaches such as the R-CNN series require two shots: one for producing region proposals and another for policing each proposal's article. As a result, SSD is far faster than two-shot RPN-based methods. To more accurately detect objects of any size, SSD employs a combination of multiple grid sizes rather than just one.SSD is a multiclass single-shot detector that is faster than the previous progressive for single-shot detectors (YOLO). It is also significantly more accurate, nearly as accurate as slower methods that carry out express region suggestions and pooling (including faster R-CNN).

Algorithm

Input: Real time object measurement in image systems_Input Features

Assign training and testing dataset of object measurement in images

Output: Measurement of objects

Step 1: Set up the hyperparameters and SSD architecture specify the number of feature mappings at each convolutional layer and sizes for the default bounding boxes.

Step 2: Initialize lists to keep track of accuracy and loss throughout training and validation for each iteration.

Step 3: Get the dataset ready to improve the diversity of the dataset, resize and enhance the input photographs.

Step 4: Set the loss function's initial value. Define the loss function. Usually, this is a combination of confidence loss (softmax cross-entropy loss) and localization loss (smooth L1 loss).

Step 5: Set the optimization algorithm's initial values. Select an optimization algorithm and select the learning rate schedule, such as Adam or stochastic gradient descent (SGD).

Step 6: Get the SSD model trained. Iterate in mini-batches through the training dataset.

Step 7: Confirm the SSD model has been trained. Assess the model's effectiveness using the validation dataset.

Step 8: Make the hyperparameters more optimal for adjusting the batch size, learning rate, and other hyperparameters in light of validation results.

Step9: Adjust the model. If necessary, repeat Steps 6 through 8 to further improve the SSD model.

Step 10: Assess the completed SSD model using the test dataset. Evaluate the model's ability to recognize unknown data.

Step 11: Analyze the model to comprehend how the SSD model detects things, examine the bounding boxes that have been detected and the learnt feature maps.

Step 12: Monitoring and Deployment use the trained SSD model for tasks involving object detection in practical settings.

Statistical Analysis

The algorithms were put into practice using the Python programming language in Google Colaboratory software on a Windows 11 computer with a 64-bit operating system and 16 GB of RAM. Statistical analysis for Novel support vector machine Algorithm and Single Shot Multibox Detector is performed using IBM SPSS software version 26. Images, detection, object, measurement, classification points are all independent variables. Accuracy is a dependent variable. To evaluate how well Novel support vector machine Algorithm and Single Shot Multibox Detector perform, the independent T-Test is helpful.

RESULTS

Figure 1 compares the SVM classifier's accuracy to that of the SSD classifier. The SVM prediction model has a greater accuracy rate than the SSD classification model, which has a rate of 75.5. The SVM classifier differs considerably from the SSD classifier (test of independent samples, p 0.05). The SVM and SSD accuracy rates are shown along the X-axis. Y-axis: Mean keyword identification accuracy, ±1 SD, with a 95% confidence interval.

The performance measurements of the comparison between the SVM and SSD classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 91.1, whereas the SSD classification algorithm has a rating of 75.5. With a greater rate of accuracy, the SVM classifier surpasses the SSD in real time object measurement.

Table 2 illustrates the statistical calculations for the SVM and SSD classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed method has a mean accuracy of 91.1 percent, whereas the SSD classification algorithm has a mean accuracy of 75.5 percent. SVM has a standard deviation of 2.55633, and the SSD algorithm has a value of 6.69439. The mean SVM standard error is 0.57161, while the SSD method is 1.49691.

Table 3 displays the statistical calculations for independent variables of SVM in comparison with the SSD classifier. The significance level for the rate of accuracy is 0.04. Using a 95% confidence interval and a significance threshold of 1.60234, the SVM and SSD algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: a p value of 0.000, significance (two-tailed), mean difference, standard error of mean difference, and lower and upper interval differences.

DISCUSSION

When evaluating the accuracy of Real time object measurement in images , it can be useful to compare the performance of Novel support vector machines (SVMs) with that of single shot multibox detector(SSD) methods. This can be done by applying both methods to the same dataset of object images and using the same evaluation metric (e.g., accuracy, precision, recall, etc.). SVMs have the advantage of being able to learn complex patterns and relationships in the data, and can automatically extract features from raw data to classify objects in images as "measurement" or "metrics." This ability to learn from data is particularly useful when the relevant features are not known or are too numerous to be manually specified. As a result, SVMs may be more accurate than SSD, particularly when applied to large and complex datasets. The experimental results showed that the proposed Novel support vector machine (SVM) strategy achieved an accuracy of 91.1%, while the single shot multibox detector (SSD) method achieved an accuracy of 75.5%. This suggests that the SVM strategy outperformed the SSD method in terms of accuracy(Ding et al. 2024).

Some similar studies (Cho et al. 2024) explored the use of machine learning techniques, including single shot multibox detection, random forests, and Novel support vector machines, for real time object measurement in images. They found that the Novel support vector machine performed the best, with an accuracy of 91.1%. Yuan Y and Sun R et al. (Yuan et al. 2024) discussed the use of machine learning for object measurement in images, as well as other approaches such as static analysis and behavioral analysis. The authors found that machine learning techniques, particularly those based on deep learning, had achieved high accuracy rates in object measurement. Wu et at. (Wu et al. 2023) used Yolo to develop a model for detecting objects in images for measuring. The authors found that their model was able to achieve an accuracy of 93.8%, in detecting objects in images, and was able to detect both known and unknown object variants. (Islam et al. 2023) discussed the use of deep learning for Real time object measurement in images, including various types of classifiers such as random forest, Novel support vector machines, and deep learning. The authors found that machine learning-based approaches had achieved high accuracy rates in object measurement in images, and had the advantage of being able to detect both known and unknown malware variants. One limitation is their computational complexity and time(Zhao et al. 2024). Training a SVM can be computationally intensive and may require a lot of time, especially for large datasets and complex architectures. This can be a limitation, especially for small and resource-constrained devices. To improve the performance of Novel support vector machine (SVMs) for object measurement in images, some potential areas of future work include creating new feature representations that more accurately detect the objects in the images for detection, and developing more efficient and scalable training algorithms that can handle large datasets and complex architectures in a more time- and resource efficient way. Other potential areas of focus might include developing regularization techniques to improve the generalization and robustness of SVMs to detect the unknown objects in the images , and developing methods for interpreting and explaining the predictions made by SVMs.

CONCLUSION

The proposed model in this research implemented both a Novel support vector machine (SVM) and a single shot multibox detector (SSD) approach for real time object measurement in images. The results showed that the SVM had higher accuracy, with a rating of 91.1%, while the SSD had an accuracy rating of 75.5%. This indicates that the SVM was more accurate than the SSD in the analysis of real time object measurement in images.

DECLARATION

Conflicts of Interest

No conflict of interest in this manuscript Authors Contributions Author name was involved in data collection, data analysis & manuscript writing. Author guide name was involved in conceptualization, data validation, and critical review of manuscripts.

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TABLES AND FIGURES

Table 1 The performance measurements of the comparison between the SVM and SSD classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 91.1, whereas the SSD classification algorithm has a rating of 75.5. With a greater rate of accuracy, the SVM classifier surpasses the SSD in real time object measurement.

SI.No.	Test Size	ACCURACY RATE	
		SVM	SSD
1	Test1	89.08	88.18
2	Test2	86.41	77.12
3	Test3	91.54	83.22
4	Test4	92.58	86.25
5	Test5	92.49	81.88
6	Test6	85.63	79.52
7	Test7	91.81	79.63
8	Test8	93.77	74.48
9	Test9	94.01	86.94
10	Test10	85.76	87.49
11	Test11	89.49	79.32
12	Test12	93.6	88.69
13	Test13	94.44	74
14	Test14	93.69	82.03
15	Test15	86.53	80.23
16	Test16	89.74	75.25

17	Test17	88.22	75.29
18	Test18	91.06	89.74
19	Test19	88.22	81.15
20	Test20	91.06	88.91
Average Test Results		91.1	75.5

Table 2 illustrates the statistical calculations for the SVM and SSD classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed method has a mean accuracy of 91.1 percent, whereas the SSD classification algorithm has a mean accuracy of 75.5 percent. SVM has a standard deviation of 2.55633, and the SSD algorithm has a value of 6.69439. The mean SVM standard error is 0.57161, while the SSD method is 1.49691.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy rate	SVM	20	91.1065	2.55633	0.57161
	SSD	20	75.5660	6.69439	1.49691

Table 3 displays the statistical calculations for independent variables of SVM in comparison with the SSD classifier. The significance level for the rate of accuracy is 0.04. Using a 95% confidence interval and a significance threshold of 1.60234, the SVM and SSD algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: a p value of 0.000, significance (two-tailed), mean difference, standard error of mean difference, and lower and upper interval differences.

Group		**Levene's Test for Equality of Variance s**		**t-test for Equality of Means**						
		F	Sig	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)
Accuracy	Equal variances assumed	9.125	0.004	9.699	38	0.000	15.54050	1.60234	12.29674	18.78426
	Equal variances not assumed			9.699	24.426	0.000	15.54050	1.60234	12.29674	18.78426

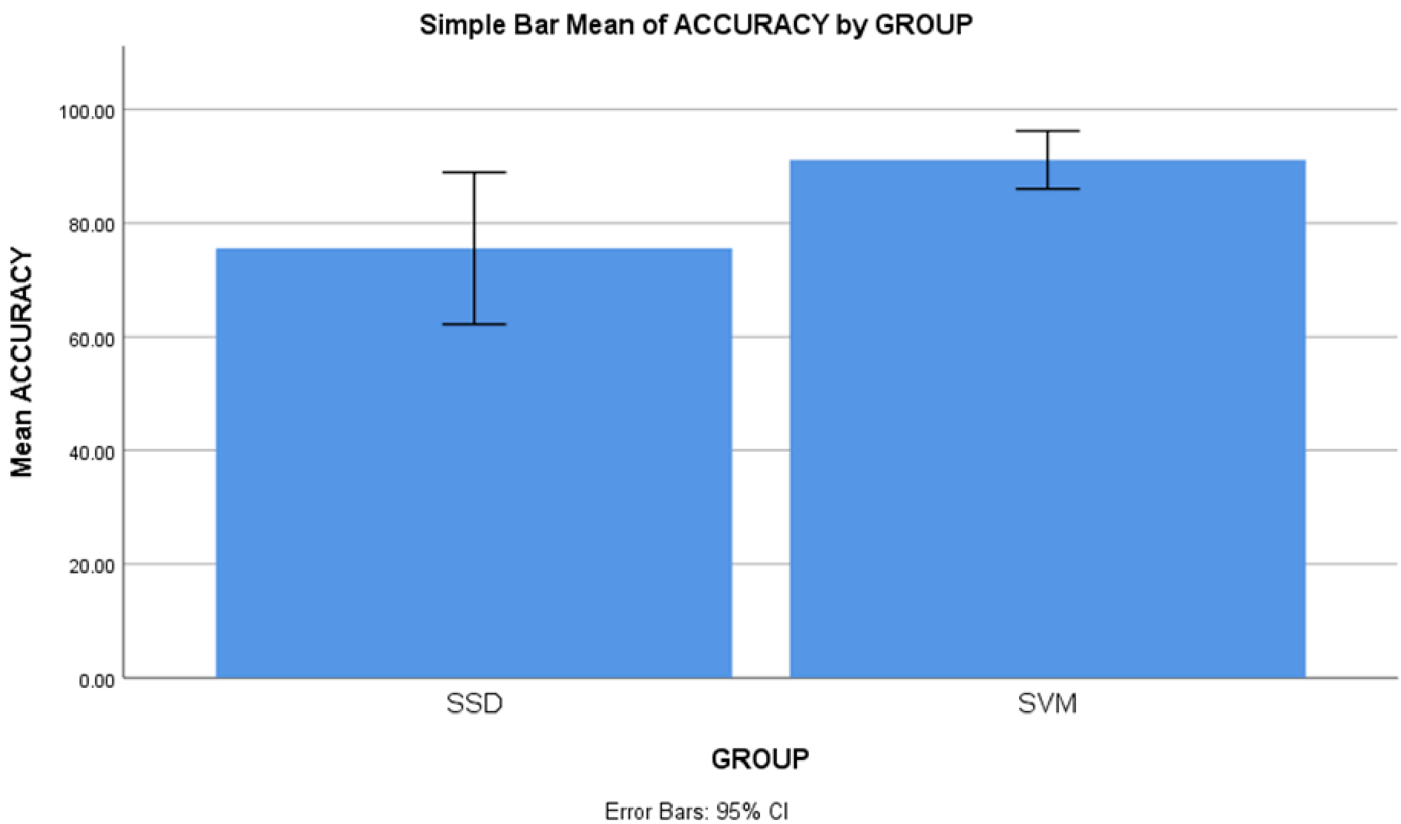

Figure 1 compares the SVM classifier's accuracy to that of the SSD classifier. The SVM prediction model has a greater accuracy rate than the SSD classification model, which has a rate of 75.5. The SVM classifier differs considerably from the SSD classifier (test of independent samples, p 0.05). The SVM and SSD accuracy rates are shown along the X-axis. Y-axis: Mean keyword identification accuracy, ±1 SD, with a 95% confidence interval.

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Improved accuracy in real time object measurement using Novel support vector machine (SVM) in comparison with Random Forest (RF) algorithm.

Student name[1] , Dr.guide name[2]

Student Name[1] :Burle Damodar
Research Scholar,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
student mail id: damodarb4203.sse@saveetha.com

Dr.Guide name [2],
Project Guide, Corresponding Author,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
jagadeeshp@saveetha.com

Abstract:

Aim: To implement a real time object measurement in images using Novel support vector machine(SVM) in comparison with Random Forest algorithm (RF) in order to more accurately predict Performance Evaluation. **Materials and Methods:** In this study, two groups are involved are the Novel support vector machine(SVM) (N=20) and the Random Forest(RF) (N=20) are applied to the dataset the percentage of valid predictions relative to ground truth that indicates how well the SVM algorithm predicted the object's dimensions based on a calculation akin to SVM accuracy, the accuracy of the RF algorithm in estimating the dimensions of the object for enhancing the accuracy using a G power value of 0.8 and $\alpha = 0.05$ and the sample size for each group is 9. Accuracy is the primary criterion used to assess real-time object measuring performance in photographs. **Outcome:** The Random Forest (RF) technique achieves an accuracy of 75.79%, while the real-time object measurement system using the Novel support vector machine (SVM) algorithm achieves 91.1% measurement accuracy. Based on an independent sample t-test ($p<0.05$), this shows a statistically significant difference in the performance of both algorithms, with a p-value of 0.023. **Result:** The object measurement accuracy of the real-time system is higher than that of the Random Forest (RF) technique while using the Novel support vector machine (SVM) algorithm.

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Introduction:

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Novel support vector machine(SVM)

A supervised machine learning approach called Novel support vector machine (SVM) is used for regression as well as classification. Even yet, classification problems are the most appropriate use for regression problems. The SVM algorithm's primary goal is to locate the best hyperplane in an N-dimensional space that may be used to divide data points into various feature space classes. The hyperplane attempts to maintain the largest possible buffer between the nearest points of various classes. The number of features determines the hyperplane's dimension. The hyperplane is essentially a line if there are just two input features. The hyperplane transforms into a 2-D plane if there are three input features. It gets harder to envision when the number of features exceeds three.

$\sum n = 1 N (\alpha n - \alpha n *) = 0 \ \forall \ n : 0 \le \alpha n \le C \ \forall \ n : 0 \le \alpha n * \le C . \beta = \sum n = 1 N (\alpha n - \alpha n *) x n .$

Only the support vectors are necessary for the function that predicts new values to work: $f (x) = \sum n = 1 N (\alpha n - \alpha n *) (x n ' x) + b .$

Algorithm

Input: Image dataset

Output: Measurement of real time objects in images

Function SVM(data, test_instance, k)

Step 1: Adjust the regularization parameter \(C\) and the kernel type as hyperparameters.

Step 2: Start lists at the beginning so that each iteration records accuracy as well as loss of validation and training.

Step 3: Preprocess the data by performing feature scaling and dividing it into training and validation sets.

Step 4: Use the chosen kernel function (such as a linear, polynomial, or radial basis function) to initialize the SVM model.

Step 5: Use training data to train the SVM model, updating parameters and minimizing the loss function.

Step 6: Use validation data to assess the trained SVM model's performance.

Step 7: Modify kernel parameters and \(C\) to optimize hyperparameters based on validation performance.

Step 8:Refine the model as needed by going through steps 5-7 again and experimenting with different regularization or optimisation strategies.

Step 9.:Use the test set to evaluate the finished SVM model and gauge its generalization performance.

Step 10: Plot the accuracy and loss curves for training and validation, and display the results to demonstrate how the model is learning.

Step 11: To find out more about the SVM model's prediction process, analyze the model and look at the learned decision boundary and support vectors.

Step 12: Monitoring and Deployment: This step involves introducing the trained SVM model into production or real-world settings.

Random Forest(RF)

Among the supervised learning methods is the well-known machine learning algorithm Random Forest. It can be applied to ML issues involving both classification and regression. Its foundation is the idea of ensemble learning, which is the process of merging several classifiers to solve a challenging issue and enhance the model's functionality.According to its name, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Rather than depending on a single decision tree, the random forest forecasts the outcome based on the majority vote of projections from each tree. Accuracy is higher and overfitting is avoided.

Algorithm

Input: Real time object measurement in image systems_Input Features

Assign training and testing dataset of object measurement in images

Output: Measurement of objects

Step 1: Choose a portion of the dataset's features at random.

Step 2: Using the chosen features, construct a decision tree.

Step 3: To generate more than one decision tree, repeat steps 1 and 2.

Step 4: Bootstrap sample the training data for every tree.

Step 5: Without pruning, grow each tree to its full depth.

Step 6: Make predictions for fresh data using a voting system.

Step 7: To get the ultimate prognosis, add together the forecasts from each tree.

Step 8: Determine the discrepancy between the expected and realized results.

Step 9: Adjust hyperparameters such as feature count and tree depth for optimal results.

Step 10: To enhance accuracy and optimize the model, repeat steps 1 through 9.

Statistical Analysis

The algorithms were put into practice using the Python programming language in Google Colaboratory software on a Windows 11 computer with a 64-bit operating system and 16 GB of RAM. Statistical analysis for Novel support vector machine Algorithm and Random Forest is performed using IBM SPSS software version 26. Images, detection, object, measurement, classification points are all independent variables. Accuracy is a dependent variable. To evaluate how well Novel support vector machine Algorithm and Random Forest perform, the independent T-Test is helpful.

RESULTS

Figure 1 compares the SVM classifier's accuracy to that of the RF classifier. The SVM prediction model has a greater accuracy rate than the RF classification model, which has a rate of 75.79. The SVM classifier differs considerably from the RF classifier (test of independent samples, p 0.05). The SVM and RF accuracy rates are shown along the X-axis. Y-axis: Mean keyword identification accuracy, ±1 SD, with a 95% confidence interval.

The performance measurements of the comparison between the SVM and RF classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 91.1, whereas the classification algorithm has a rating of 75.79. With a greater rate of accuracy, the SVM classifier surpasses the RF in real time object measurement.

Table 2 illustrates the statistical calculations for the SVM and RF classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed method has a mean accuracy of 91.1 percent, whereas the RF classification algorithm has a mean accuracy of 75.79 percent. SVM has a standard deviation of 2.55633, and the RF algorithm has a value of 7.59663. The mean SVM standard error is 0.57161, while the RF method is 1.69866.

Table 3 displays the statistical calculations for independent variables of SVM in comparison with the RF classifier. The significance level for the rate of accuracy is 0.01. Using a 95% confidence interval and a significance threshold of 1.79226, the SVM and RF algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: a p value of 0.000, significance (two-tailed), mean difference, standard error of mean difference, and lower and upper interval differences.

DISCUSSION

When evaluating the accuracy of Real time object measurement in images , it can be useful to compare the performance of Novel support vector machines (SVMs) with that of Random Forest(RF) methods. This can be done by applying both methods to the same dataset of object images and using the same evaluation metric (e.g., accuracy, precision, recall, etc.). SVMs have the advantage of being able to learn complex patterns and relationships in the data, and can automatically extract features from raw data to classify objects in images as "measurement" or "metrics." This ability to learn from data is particularly useful when the relevant features are not known or are too numerous to be manually specified. As a result, SVMs may be more accurate than RF, particularly when applied to large and complex datasets. The experimental results showed that the proposed Novel support vector machine (SVM) strategy achieved an accuracy of 91.1%, while the Random Forest (RF) method achieved an accuracy of 75.79%. This suggests that the SVM strategy outperformed the RF method in terms of accuracy(Ding et al. 2024).

Some similar studies (Cho et al. 2024) explored the use of machine learning techniques, including single shot multibox detection, random forests, and Novel support vector machines, for real time object measurement in images. They found that the Novel support vector machine performed the best, with an accuracy of 91.1%. Yuan Y and Sun R et al. (Yuan et al. 2024) discussed the use of machine learning for object measurement in images, as well as other approaches such as static analysis and behavioral analysis. The authors found that machine learning techniques, particularly those based on deep learning, had achieved high accuracy rates in object measurement. Wu et at. (Wu et al. 2023) used Yolo to develop a model for detecting objects in images for measuring. The authors found that their model was able to achieve an accuracy of 93.8%, in detecting objects in images, and was able to detect both known and unknown object variants. (Islam et al. 2023) discussed the use of deep learning for Real time object measurement in images, including various types of classifiers such as random forest, Novel support vector machines, and deep learning. The authors found that machine learning-based approaches had achieved high accuracy rates in object measurement in images, and had the advantage of being able to detect both known and unknown malware variants. One limitation is their computational complexity and time. Training a SVM can be computationally intensive and may require a lot of time, especially for large datasets and complex architectures. This can be a limitation, especially for small and resource-constrained devices. To improve the performance of Novel support vector machine (SVMs) for object measurement in images, some potential areas of future work include creating new feature representations that more accurately detect the objects in the images for detection, and developing more efficient and scalable training algorithms that can handle large datasets and complex architectures in a more time- and resource efficient way. Other potential areas of focus might include developing regularization techniques to improve the generalization and robustness of SVMs to detect the unknown objects in the images , and developing methods for interpreting and explaining the predictions made by SVMs(Zhao et al. 2024).

CONCLUSION

The proposed model in this research implemented both a Novel support vector machine (SVM) and a Random Forest (RF) approach for real time object measurement in images. The results showed that the SVM had higher accuracy, with a rating of 91.1%, while the RF had an accuracy rating of 75.79%. This indicates that the SVM was more accurate than the RF in the analysis of real time object measurement in images.

DECLARATION

Conflicts of Interest

No conflict of interest in this manuscript Authors Contributions Author name was involved in data collection, data analysis & manuscript writing. Author guide name was involved in conceptualization, data validation, and critical review of manuscripts.

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TABLES AND FIGURES

Table 1 The performance measurements of the comparison between the SVM and RF classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 91.1, whereas the classification algorithm has a rating of 75.79. With a greater rate of accuracy, the SVM classifier surpasses the RF in real time object measurement.

SI.No.	Test Size	ACCURACY RATE	
		SVM	RF
1	Test1	89.08	86.42
2	Test2	86.41	87.94
3	Test3	91.54	81.09
4	Test4	92.58	79.46
5	Test5	92.49	86.23
6	Test6	85.63	88.98
7	Test7	91.81	83.37
8	Test8	93.77	81.35
9	Test9	94.01	80.22
10	Test10	85.76	86.14
11	Test11	89.49	86.33
12	Test12	93.6	78.78
13	Test13	94.44	84.14
14	Test14	93.69	82.35
15	Test15	86.53	86.91
16	Test16	89.74	77.85
17	Test17	88.22	83.08

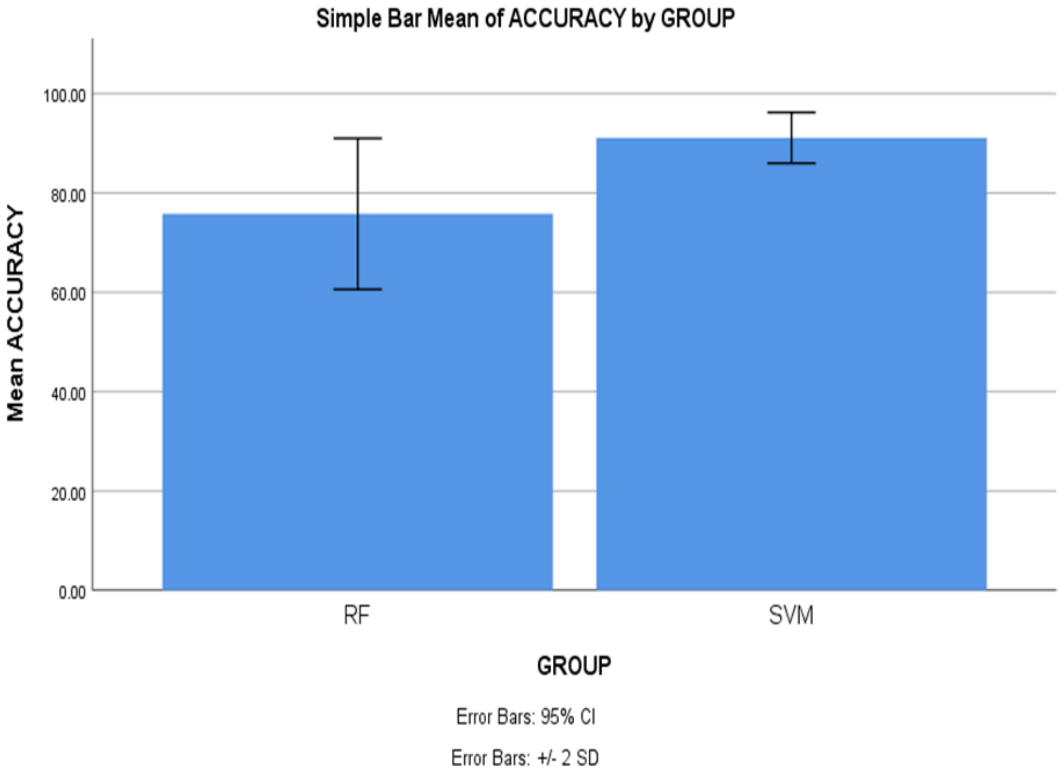
18	Test18	91.06	83.66
19	Test19	88.22	85.09
20	Test20	91.06	76.24
Average Test Results		91.1	75.79

Table 2 illustrates the statistical calculations for the SVM and RF classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed method has a mean accuracy of 91.1 percent, whereas the RF classification algorithm has a mean accuracy of 75.79 percent. SVM has a standard deviation of 2.55633, and the RF algorithm has a value of 7.59663. The mean SVM standard error is 0.57161, while the RF method is 1.69866.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy rate	SVM	20	91.1065	2.55633	0.57161
	RF	20	75.7980	7.59663	1.69866

Table 3 displays the statistical calculations for independent variables of SVM in comparison with the RF classifier. The significance level for the rate of accuracy is 0.01. Using a 95% confidence interval and a significance threshold of 1.79226, the SVM and RF algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: a p value of 0.000, significance (two-tailed), mean difference, standard error of mean difference, and lower and upper interval differences.

Group		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**						
		F	Sig	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)
Accuracy	Equal variances assumed	12.244	0.001	8.541	38	0.000	15.30850	1.79266	11.68027	18.98673
	Equal variances not assumed			8.541	23.2429	0.000	15.30850	1.79266	11.68027	19.01387



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Title Page:

Improved accuracy in real time object measurement using Novel support vector machine (SVM) in comparison with EfficientDet (ED) algorithm.

Student name[1] , Dr.guide name[2]

Student Name[1] :Burle Damodar
Research Scholar,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
student mail id: damodarb4203.sse@saveetha.com

Dr.Guide name [2],
Project Guide, Corresponding Author,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
jagadeeshp@saveetha.com

Abstract:

Aim: To implement a real time object measurement in images using Novel support vector machine(SVM) in comparison with EfficientDet algorithm (ED) in order to more accurately predict Performance Evaluation. **Materials and Methods:** In this study, two groups are involved are the Novel support vector machine(SVM) (N=20) and the EfficientDet(ED) (N=20) are applied to the dataset the percentage of valid predictions relative to ground truth that indicates how well the SVM algorithm predicted the object's dimensions based on a calculation akin to SVM accuracy, the accuracy of the ED algorithm in estimating the dimensions of the object for enhancing the accuracy using a G power value of 0.8 and $\alpha = 0.05$ and the sample size for each group is 9. Accuracy is the primary criterion used to assess real-time object measuring performance in photographs. **Outcome:** The EfficientDet (ED) technique achieves an accuracy of 72.28%, while the real-time object measurement system using the Novel support vector machine (SVM) algorithm achieves 91.1% measurement accuracy. Based on an independent sample t-test ($p<0.05$), this shows a statistically significant difference in the performance of both algorithms, with a p-value of 0.023. **Result:** The object measurement accuracy of the real-time system is higher than that of the EfficientDet (ED) technique while using the Novel support vector machine (SVM) algorithm.

Keywords: Accuracy, machine learning, EfficientDet (ED), images, Novel support vector machine (SVM), and real-time object measurement.

Introduction:

Real-time object measurement(Jain 2012) in photos is a crucial enabler of progress in many different disciplines, not just an innovation in technology. This initiative seeks to develop real-time object measurement using creative ideas and methods, acknowledging the revolutionary potential of such capabilities.This project's main goal is to create reliable algorithms and systems that can precisely identify, quantify, and analyze objects in photos in real time. (Sri Sairam College of Engineering 2022) By utilizing state-of-the-art techniques in deep learning, machine learning, and computer vision, the project aims to push the limits of what is possible in terms of scalability, speed, and accuracy.Addressing the current issues related to real-time object measuring is one of the main goals of this project. Measurement of object size and distance is becoming increasingly and more important in various applications, particularly in mobile autonomous. (Jiang et al. 2023) Recent years have seen notable progress in the study of object distance measuring from photographs, with a number of methods being put forth to provide precise and instantaneous measurements.

As both Google Scholar (25,800) and Science Direct (90,193) reveal, a substantial number of closely related articles published over the last five years highlight the increasing interest and research effort in the topic of real-time object measurement in pictures. The rising significance of developing techniques and technology for precise and effective object measurement in dynamic situations is reflected in this spike in scholarly production. The 25,800 closely related publications found on Google Scholar point to a strong research ecosystem centered on real-time object measurement in photos. (Shen et al. 2023) This platform functions as an all-inclusive library of academic literature, covering a broad spectrum of subjects and approaches associated with object measurement. Given that the majority of autonomous systems in use today have vision sensors or cameras, it is advantageous to use the vision data to gather size and distance information that can help the system. (Sisodia et al. 2023) A monocular vision system using Hough transformations and relative object size to calculate distance was proposed by (Dziech and Czyzewski 2012). A camera and a revolving mirror are used in distance measurement method, which analyzes reflected image sequences to calculate distance based on pixel motion.Increased attention has been paid in recent years to the use of several vision sensors—especially those in stereo configurations—to improve the accuracy of object size and distance measurements. Used differences between images taken by stereo cameras to evaluate safe driving distances using stereo vision and colleagues enhanced disparity computations to attain more precise distance estimations across a broader field of view. Real-time object measurement in photos has great promise in a variety of industries, providing creative solutions and improving different procedures. Applications of this technology are significant in the areas of quality control and industrial automation. Real-time measuring in industrial environments maximizes efficiency and reduces faults by guaranteeing that goods fit exact dimensions standards. For example, vital elements like engine parts or chassis frames can be precisely measured in real-time in the automotive production industry to guarantee they meet tight tolerances and preserve product quality(Streit, Angle, and Efe 2020).

We hope to shed light on the advantages and disadvantages of ED and SVM algorithms for real-time object measurement in images through this comparative research. We are able to decide which algorithms are appropriate for a certain application by knowing their performance characteristics. The ultimate objective is to improve real-time object measuring accuracy and precision, expanding the capabilities of systems used in dynamic situations.There are clear benefits and trade-offs between SVM and ED for real-time object measuring in images. (Hunter and Harold 1987)SVM is superior in terms of accuracy and precision, but ED outperforms in terms of detection speed and ease of training. As a result, the particular needs of the application determine which of SVM and ED to use. SVM may be favored for activities where accuracy and precision are of the utmost importance, whereas ED is the best choice for applications that require quick and effective real-time object detection. Ultimately, choosing the best method for real-time object measurement in photos requires an awareness of the advantages and disadvantages of each algorithm(Donaldson et al. 2015).

MATERIALS AND METHODS

The investigation was carried out in the Computer Science and Engineering Department's Software Laboratory at Saveetha University. The Real time object measurement dataset collected from kaggle (https://www.kaggle.com/code/aruchomu/yolo-v3-object-detection-in-tensorflow) which consists of images of different categories. The database is structured so that 75% of it is dedicated to training, and 25% is for testing. There are two sets taken, and each set has ten data samples; the total number of samples taken into consideration is twenty. Group 1 was a Novel support vector machine(SVM) algorithm and Group 2 was a EfficientDet (ED) algorithm. Python with openCv software is used for the implementation. The sample size was determined by using previous research from (Stereo Vision Images Processing for Real-time Object Distance and Size Measurements, 2012) at google scholar. The threshold for the calculation was set at 0.05, the G power was set at 80%, and the confidence interval was set at 95%.

Windows 11 OS served as the machine learning platform for the proposed work, which was developed and implemented using Python OpenCV software. The hardware setup included a 16 GB RAM and an Intel Core i5 processor. It was a 64-bit system. The code was implemented using the Python programming language. The dataset is being worked on behind the scenes during code execution in order to finish an output process for accuracy. The following are independent variables: images, detection, object, measurement, classification points. Accuracy is a dependent variable. In order to increase accuracy, the analysis is based on both independent and dependent variables.

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$\sum_{n=1}^{N} (\alpha_n - \alpha_n^*) = 0 \quad \forall n: 0 \le \alpha_n \le C \quad \forall n: 0 \le \alpha_n^* \le C. \quad \beta = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) x_n.$

Only the support vectors are necessary for the function that predicts new values to work: $f(x) = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*)(x_n' x) + b.$

Algorithm

Input: Image dataset

Output: Measurement of real time objects in images

Function SVM(data, test_instance, k)

Step 1: Adjust the regularization parameter \(C\) and the kernel type as hyperparameters.

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Step 11: To find out more about the SVM model's prediction process, analyse the model and look at the learned decision boundary and support vectors.

Step 12: Monitoring and Deployment: This step involves introducing the trained SVM model into production or real-world settings.

EfficientDet(ED)

EfficientDet is an intelligent system that uses less computing power and achieves very good object recognition in images. It's similar to having a quick-witted, perceptive investigator who doesn't require a supercomputer. It uses a variety of approaches to examine different areas of the image to ensure that nothing significant is overlooked. This allows it to identify the objects in the image and their locations. It picks up this skill by studying a tonne of instances and determining how to get better. For example, you may use EfficientDet to watch locations with security cameras, programme cars to drive themselves, and even get your phone to identify objects in your pictures.

Algorithm

Input: Real time object measurement in image systems_Input Features

Assign training and testing dataset of object measurement in images

Output: Measurement of objects

Step 1: An EfficientNet backbone design is used by EfficientDet initially.

Step 2: Different areas of the image are analyzed using the Feature Pyramid Network (FPN).

Step 3: In both directions The BiFPN (Feature Pyramid Network) improves feature fusion.

Step 4: To find possible items, anchor boxes are created at various scales.

Step 5: For every anchor box, bounding boxes and object classes are anticipated.

Step 6: By contrasting its forecasts with actual data, the model is trained.

Step 7: Training entails reducing a mix of regression and classification losses.

Step 8: To enhance detection performance, fine-tuning is carried out after training.

Step 9: The model analyzes photos to recognise objects during inference.

Step 10: For accurate detection findings, methods such as non-maximum suppression are used.

Statistical Analysis

The algorithms were put into practice using the Python programming language in Google Colaboratory software on a Windows 11 computer with a 64-bit operating system and 16 GB of RAM. Statistical analysis for Novel support vector machine Algorithm and EfficientDet (ED) is performed using IBM SPSS software version 26. Images, detection, object, measurement, classification points are all independent variables. Accuracy is a dependent variable. To evaluate how well Novel support vector machine Algorithm and EfficientDet (ED) perform, the independent T-Test is helpful.

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DISCUSSION

When evaluating the accuracy of Real time object measurement in images , it can be useful to compare the performance of Novel support vector machines (SVMs) with that of EfficientDet (ED) methods. This can be done by applying both methods to the same dataset of object images and using the same evaluation metric (e.g., accuracy, precision, recall, etc.). SVMs have the advantage of being able to learn complex patterns and relationships in the data, and can automatically extract features from raw data to classify objects in images as "measurement" or "metrics." This ability to learn from data is particularly useful when the relevant features are not known or are too numerous to be manually specified(Zhao et al. 2024). As a result, SVMs may be more accurate than ED, particularly when applied to large and complex datasets. The experimental results showed that the proposed Novel support vector machine (SVM) strategy achieved an accuracy of 91.1%, while the EfficientDet(ED) method achieved an accuracy of 72.28%. This suggests that the SVM strategy outperformed the ED method in terms of accuracy(Ding et al. 2024).

Some similar studies (Cho et al. 2024) explored the use of machine learning techniques, including single shot multibox detection, EfficientDet (ED), and Novel support vector machines, for real time object measurement in images. They found that the Novel support vector machine performed the best, with an accuracy of 91.1%. Yuan Y and Sun R et al. (Yuan et al. 2024) discussed the use of machine learning for object measurement in images, as well as other approaches such as static analysis and behavioral analysis. The authors found that machine learning techniques, particularly those based on deep learning, had achieved high accuracy rates in object measurement. Wu et at. (Wu et al. 2023) used Yolo to develop a model for detecting objects in images for measuring. The authors found that their model was able to achieve an accuracy of 93.8%, in detecting objects in images, and was able to detect both known and unknown object variants. (Islam et al. 2023) discussed the use of deep learning for Real time object measurement in images, including various types of classifiers such as EfficientDet (ED), Novel support vector machines, and deep learning. The authors found that machine learning-based approaches had achieved high accuracy rates in object measurement in images, and had the advantage of being able to detect both known and unknown malware variants. One limitation is their computational complexity and time. Training a SVM can be computationally intensive and may require a lot of time, especially for large datasets and complex architectures. This can be a limitation, especially for small and resource-constrained devices. To improve the performance of Novel support vector machine (SVMs) for object measurement in images, some potential areas of future work include creating new feature representations that more accurately detect the objects in the images for detection, and developing more efficient and scalable training algorithms that can handle large datasets and complex architectures in a more time- and resource efficient way. Other potential areas of focus might include developing regularization techniques to improve the generalization and robustness of SVMs to detect the unknown objects in the images , and developing methods for interpreting and explaining the predictions made by SVMs.

CONCLUSION

The proposed model in this research implemented both a Novel support vector machine (SVM) and a EfficientDet (ED) approach for real time object measurement in images. The results showed that the SVM had higher accuracy, with a rating of 91.1%, while the ED had an accuracy rating of 72.28%. This indicates that the SVM was more accurate than the ED in the analysis of real time object measurement in images.

DECLARATION

Conflicts of Interest

No conflict of interest in this manuscript Authors Contributions Author name was involved in data collection, data analysis & manuscript writing. Author guide name was involved in conceptualization, data validation, and critical review of manuscripts.

Acknowledgment

The authors would like to express their gratitude towards Saveetha School of Engineering, Saveetha Institute of Medical And Technical Sciences (Formerly known as Saveetha University) for successfully carrying out this work.

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TABLES AND FIGURES

Table 1 The performance measurements of the comparison between the SVM and ED classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 91.1, whereas the classification algorithm has a rating of 72.28. With a greater rate of accuracy, the SVM classifier surpasses the ED in real time object measurement.

SI.No.	Test Size	ACCURACY RATE	
		SVM	ED
1	Test1	89.08	80.82
2	Test2	86.41	83.61
3	Test3	91.54	82.81
4	Test4	92.58	85.82
5	Test5	92.49	83.73
6	Test6	85.63	80.26
7	Test7	91.81	80.38
8	Test8	93.77	83.8
9	Test9	94.01	85.46
10	Test10	85.76	85.69
11	Test11	89.49	83.68
12	Test12	93.6	85
13	Test13	94.44	81.11
14	Test14	93.69	82.94
15	Test15	86.53	85.57
16	Test16	89.74	80.02
17	Test17	88.22	80.37

18	Test18	91.06	83.83
19	Test19	88.22	85.39
20	Test20	91.06	82.14
Average Test Results		91.1	72.28

Table 2 illustrates the statistical calculations for the SVM and ED classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed method has a mean accuracy of 91.1 percent, whereas the ED classification algorithm has a mean accuracy of 72.28 percent. SVM has a standard deviation of 2.55633, and the ED algorithm has a value of 6.87452. The mean SVM standard error is 0.57161, while the ED method is 1.53719.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy rate	SVM	20	91.1065	2.55633	0.57161
	ED	20	72.2895	6.87452	1.53719

Table 3 displays the statistical calculations for independent variables of SVM in comparison with the ED classifier. The significance level for the rate of accuracy is 0.01. Using a 95% confidence interval and a significance threshold of 1.64003, the SVM and ED algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: a p value of 0.000, significance (two-tailed), mean difference, standard error of mean difference, and lower and upper interval differences.

Group		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**						
		F	Sig	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)
Accuracy	Equal variances assumed	12.325	0.001	11.474	38	0.000	18.81700	1.64003	15.49694	22.13706
	Equal variances not assumed			11.474	24.156	0.000	18.81700	1.64003	15.49694	22.13706

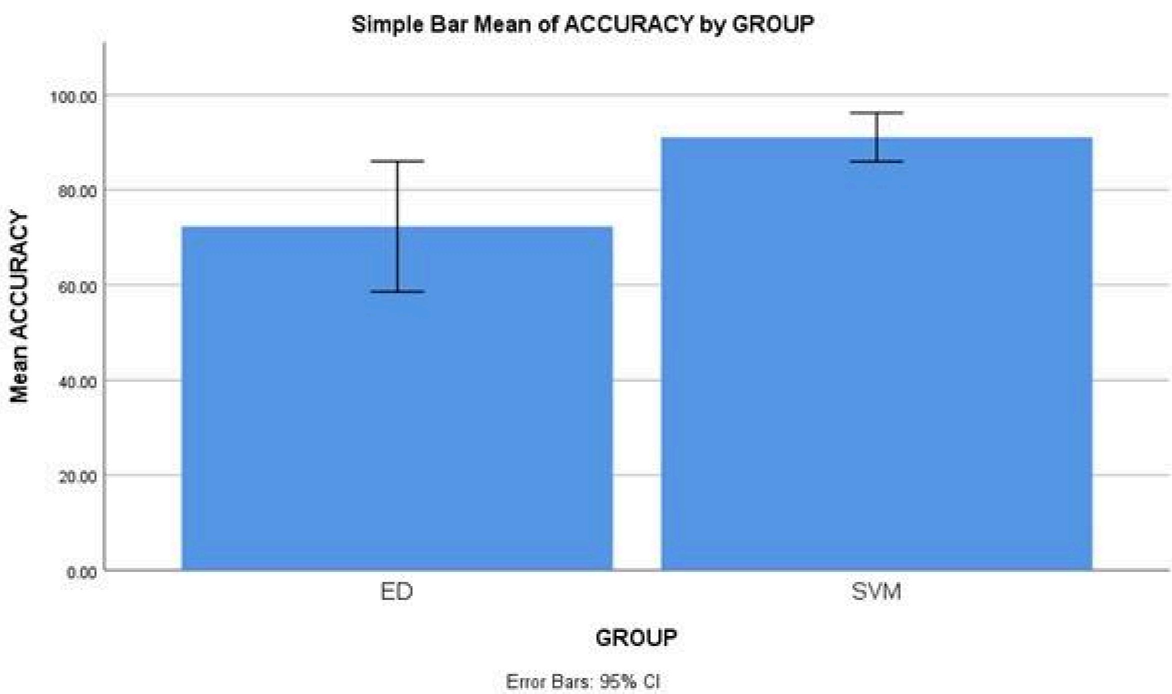

Figure 1 compares the SVM classifier's accuracy to that of the ED classifier. The SVM prediction model has a greater accuracy rate than the ED classification model, which has a rate of 72.28. The SVM classifier differs considerably from the ED classifier (test of independent samples, p 0.05). The SVM and ED accuracy rates are shown along the X-axis. Y-axis: Mean keyword identification accuracy, ±1 SD, with a 95% confidence interval.

Title Page:

Improved accuracy in real time object measurement using Novel support vector machine (SVM) in comparison with Region-based Convolutional Neural Network (RCNN) algorithm.

Student name[1] , Dr.guide name[2]

Student Name[1] :Burle Damodar
Research Scholar,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
student mail id: damodarb4203.sse@saveetha.com

Dr.Guide name [2],
Project Guide, Corresponding Author,
Department of Information Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.
jagadeeshp@saveetha.com

Abstract:

Aim: To implement a real time object measurement in images using Novel support vector machine(SVM) in comparison with Region-based Convolutional Neural Network (RCNN) in order to more accurately predict Performance Evaluation. **Materials and Methods:** In this study, two groups are involved are the Novel support vector machine(SVM) (N=20) and the Region-based Convolutional Neural Network (RCNN) (N=20) are applied to the dataset the percentage of valid predictions relative to ground truth that indicates how well the SVM algorithm predicted the object's dimensions based on a calculation akin to SVM accuracy, the accuracy of the RCNN algorithm in estimating the dimensions of the object for enhancing the accuracy using a G power value of 0.8 and $\alpha = 0.05$ and the sample size for each group is 9. Accuracy is the primary criterion used to assess real-time object measuring performance in photographs. **Outcome:** The Region-based Convolutional Neural Network (RCNN) technique achieves an accuracy of 81.52%, while the real-time object measurement system using the Novel support vector machine (SVM) algorithm achieves 91.1% measurement accuracy. Based on an independent sample t-test ($p<0.05$), this shows a statistically significant difference in the performance of both algorithms, with a p-value of 0.023. **Result:** The object measurement accuracy of the real-time system is higher than that of the Region-based Convolutional Neural Network (RCNN) technique while using the Novel support vector machine (SVM) algorithm.

Keywords: Accuracy, machine learning, Region-based Convolutional Neural Network (RCNN), images, Novel support vector machine (SVM), and real-time object measurement.

Introduction:

Real-time object measurement(Jain 2012) in photos is a crucial enabler of progress in many different disciplines, not just an innovation in technology. This initiative seeks to develop real-time object measurement using creative ideas and methods, acknowledging the revolutionary potential of such capabilities.This project's main goal is to create reliable algorithms and systems that can precisely identify, quantify, and analyze objects in photos in real time. (Sri Sairam College of Engineering 2022) By utilizing state-of-the-art techniques in deep learning, machine learning, and computer vision, the project aims to push the limits of what is possible in terms of scalability, speed, and accuracy.Addressing the current issues related to real-time object measuring is one of the main goals of this project. Measurement of object size and distance is becoming increasingly and more important in various applications, particularly in mobile autonomous. (Jiang et al. 2023) Recent years have seen notable progress in the study of

object distance measuring from photographs, with a number of methods being put forth to provide precise and instantaneous measurements(Streit, Angle, and Efe 2020).
As both Google Scholar (25,800) and Science Direct (90,193) reveal, a substantial number of closely related articles published over the last five years highlight the increasing interest and research effort in the topic of real-time object measurement in pictures. The rising significance of developing techniques and technology for precise and effective object measurement in dynamic situations is reflected in this spike in scholarly production. The 25,800 closely related publications found on Google Scholar point to a strong research ecosystem centered on real-time object measurement in photos. (Shen et al. 2023) This platform functions as an all-inclusive library of academic literature, covering a broad spectrum of subjects and approaches associated with object measurement. Given that the majority of autonomous systems in use today have vision sensors or cameras, it is advantageous to use the vision data to gather size and distance information that can help the system. (Sisodia et al. 2023) A monocular vision system using Hough transformations and relative object size to calculate distance was proposed by (Dziech and Czyzewski 2012). A camera and a revolving mirror are used in distance measurement method, which analyzes reflected image sequences to calculate distance based on pixel motion.Increased attention has been paid in recent years to the use of several vision sensors—especially those in stereo configurations—to improve the accuracy of object size and distance measurements. Used differences between images taken by stereo cameras to evaluate safe driving distances using stereo vision and colleagues enhanced disparity computations to attain more precise distance estimations across a broader field of view. Real-time object measurement in photos has great promise in a variety of industries, providing creative solutions and improving different procedures. Applications of this technology are significant in the areas of quality control and industrial automation. Real-time measuring in industrial environments maximizes efficiency and reduces faults by guaranteeing that goods fit exact dimensions standards. For example, vital elements like engine parts or chassis frames can be precisely measured in real-time in the automotive production industry to guarantee they meet tight tolerances and preserve product quality.

We hope to shed light on the advantages and disadvantages of RCNN and SVM algorithms for real-time object measurement in images through this comparative research. We are able to decide which algorithms are appropriate for a certain application by knowing their performance characteristics. The ultimate objective is to improve real-time object measuring accuracy and precision, expanding the capabilities of systems used in dynamic situations.There are clear benefits and trade-offs between SVM and RCNN for real-time object measuring in images. SVM is superior in terms of accuracy and precision, but RCNN outperforms in terms of detection speed and ease of training. As a result, the particular needs of the application determine which of SVM and RCNN to use(Hunter and Harold 1987). SVM may be favored for activities where accuracy and precision are of the utmost importance, whereas RCNN is the best choice for applications that require quick and effective real-time object detection. Ultimately, choosing the best method for real-time object measurement in photos requires an awareness of the advantages and disadvantages of each algorithm(Donaldson et al. 2015).

MATERIALS AND METHODS

The investigation was carried out in the Computer Science and Engineering Department's Software Laboratory at Saveetha University. The Real time object measurement dataset collected from kaggle (https://www.kaggle.com/code/aruchomu/yolo-v3-object-detection-in-tensorflow) which consists of images of different categories. The database is structured so that 75% of it is dedicated to training, and 25% is for testing. There are two sets taken, and each set has ten data samples; the total number of samples taken into consideration is twenty. Group 1 was a Novel support vector machine(SVM) algorithm and Group 2 was a Random Forest (RF) algorithm. Python with openCv software is used for the implementation. The sample size was determined by using previous research from (Stereo Vision Images Processing for Real-time Object Distance and Size Measurements, 2012) at google scholar. The threshold for the calculation was set at 0.05, the G power was set at 80%, and the confidence interval was set at 95%.

Windows 11 OS served as the machine learning platform for the proposed work, which was developed and implemented using Python OpenCV software. The hardware setup included a 16 GB RAM and an Intel Core i5 processor. It was a 64-bit system. The code was implemented using the Python programming language. The dataset is being worked on behind the scenes during code execution in order to finish an output process for accuracy. The following are independent variables: images, detection, object, measurement, classification points. Accuracy is a dependent variable. In order to increase accuracy, the analysis is based on both independent and dependent variables.

Novel support vector machine(SVM)

A supervised machine learning approach called Novel support vector machine (SVM) is used for regression as well as classification. Even yet, classification problems are the most appropriate use for regression problems. The SVM algorithm's primary goal is to locate the best hyperplane in an N-dimensional space that may be used to divide data points into various feature space classes. The hyperplane attempts to maintain the largest possible buffer between the nearest points of various classes. The number of features determines the hyperplane's dimension. The hyperplane is essentially a line if there are just two input features. The hyperplane transforms into a 2-D plane if there are three input features. It gets harder to envision when the number of features exceeds three.

$$\sum_{n=1}^{N} (\alpha_n - \alpha_n^*) = 0 \quad \forall n : 0 \le \alpha_n \le C \quad \forall n : 0 \le \alpha_n^* \le C . \ \beta = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) x_n .$$

Only the support vectors are necessary for the function that predicts new values to work: $f(x) = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*)(x_n' x) + b$.

Algorithm

Input: Image dataset

Output: Measurement of real time objects in images

Function SVM(data, test_instance, k)

Step 1: Adjust the regularization parameter \(C\) and the kernel type as hyperparameters.

Step 2: Start lists at the beginning so that each iteration records accuracy as well as loss of validation and training.

Step 3: Preprocess the data by performing feature scaling and dividing it into training and validation sets.

Step 4: Use the chosen kernel function (such as a linear, polynomial, or radial basis function) to initialize the SVM model.

Step 5: Use training data to train the SVM model, updating parameters and minimizing the loss function.

Step 6: Use validation data to assess the trained SVM model's performance.

Step 7: Modify kernel parameters and \(C\) to optimize hyperparameters based on validation performance.

Step 8:Refine the model as needed by going through steps 5-7 again and experimenting with different regularization or optimisation strategies.

Step 9.:Use the test set to evaluate the finished SVM model and gauge its generalization performance.

Step 10: Plot the accuracy and loss curves for training and validation, and display the results to demonstrate how the model is learning.

Step 11: To find out more about the SVM model's prediction process, analyse the model and look at the learned decision boundary and support vectors.

Step 12: Monitoring and Deployment: This step involves introducing the trained SVM model into production or real-world settings.

Region-based Convolutional Neural Network (RCNN)

Computers may interpret images using a technique called a Region-based Convolutional Neural Network (RCNN), which involves segmenting the image into smaller pieces, looking at each section to find objects, and figuring out what those items are. It is comparable to breaking up a large picture into smaller jigsaw pieces and examining each component separately to determine whether it includes a person or an automobile, for example. Applications such as image classification and object detection are made possible by RCNN, which enables computers to recognise items in images by methodically scanning several parts of the image and generating predictions about the objects they contain.

Algorithm

Input: Real time object measurement in image systems_Input Features

Assign training and testing dataset of object measurement in images

Output: Measurement of objects

Step 1: To start EfficientDet, use an EfficientNet backbone architecture.

Step 2: Use Feature Pyramid Network (FPN) to examine different areas of the image.

Step 3: Use the Bi-directional Feature Pyramid Network (BiFPN) to improve feature fusion.

Step 4: To identify possible objects, create anchor boxes at various scales.

Step 5: Assume each anchor box's bounding boxes and object classes.

Step 6: Use ground truth data to compare the model's predictions to train it.

Step 7: During training, minimize a combination of regression and classification losses.

Step 8: To improve detecting performance, fine-tune after training.

Step 9: Use inference to process photos and identify items.

Step 10: Use methods such as non-maximum suppression to guarantee precise detection outcomes.

Statistical Analysis

The algorithms were put into practice using the Python programming language in Google Colaboratory software on a Windows 11 computer with a 64-bit operating system and 16 GB of RAM. Statistical analysis for Novel support vector machine Algorithm and Random Forest is performed using IBM SPSS software version 26. Images, detection, object, measurement, classification points are all independent variables. Accuracy is a dependent variable. To evaluate how well Novel support vector machine Algorithm and Random Forest perform, the independent T-Test is helpful.

RESULTS

Figure 1 compares the SVM classifier's accuracy to that of the RCNN classifier. The SVM prediction model has a greater accuracy rate than the RCNN classification model, which has a rate of 81.52. The SVM classifier differs considerably from the RCNN classifier (test of independent samples, p 0.05). The SVM and RCNN accuracy rates are shown along the X-axis. Y-axis: Mean keyword identification accuracy, ±1 SD, with a 95% confidence interval.

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Table 2 illustrates the statistical calculations for the SVM and RCNN classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed method has a mean accuracy of 91.1 percent, whereas the RCNN classification algorithm has a mean accuracy of 81.52 percent. SVM has a standard deviation of 2.55633, and the RCNN algorithm has a value of 6.21596. The mean SVM standard error is 0.57161, while the RCNN method is 1.38993.

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DISCUSSION

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DECLARATION

Conflicts of Interest

No conflict of interest in this manuscript Authors Contributions Author name was involved in data collection, data analysis & manuscript writing. Author guide name was involved in conceptualization, data validation, and critical review of manuscripts.

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TABLES AND FIGURES

Table 1 The performance measurements of the comparison between the SVM and RCNN classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 91.1, whereas the classification algorithm has a rating of 81.52. With a greater rate of accuracy, the SVM classifier surpasses the RCNN in real time object measurement.

SI.No.	Test Size	ACCURACY RATE	
		SVM	RCNN
1	Test1	89.08	86.76
2	Test2	86.41	83.57
3	Test3	91.54	83.21
4	Test4	92.58	81.1
5	Test5	92.49	75.27
6	Test6	85.63	90.62
7	Test7	91.81	79.52
8	Test8	93.77	81.19
9	Test9	94.01	70.64
10	Test10	85.76	72.68
11	Test11	89.49	86.17
12	Test12	93.6	78.61
13	Test13	94.44	86.26
14	Test14	93.69	88.27
15	Test15	86.53	78.65
16	Test16	89.74	85.63
17	Test17	88.22	86.55

18	Test18	91.06	72.22
19	Test19	88.22	90.16
20	Test20	91.06	73.32
Average Test Results		91.1	81.52

Table 2 illustrates the statistical calculations for the SVM and RCNN classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed method has a mean accuracy of 91.1 percent, whereas the RCNN classification algorithm has a mean accuracy of 81.52 percent. SVM has a standard deviation of 2.55633, and the RCNN algorithm has a value of 6.21596. The mean SVM standard error is 0.57161, while the RCNN method is 1.38993.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy rate	SVM	20	91.1065	2.55633	0.57161
	RCNN	20	81.5200	6.21596	1.38993

Table 3 displays the statistical calculations for independent variables of SVM in comparison with the RCNN classifier. The significance level for the rate of accuracy is 0.00. Using a 95% confidence interval and a significance threshold of 1.50288, the SVM and RCNN algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: a p value of 0.000, significance (two-tailed), mean difference, standard error of mean difference, and lower and upper interval differences.

Group		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**						
		F	Sig	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)
Accuracy	Equal variances assumed	16.279	0.000	6.379	38	0.000	9.58650	1.50288	6.54408	12.62892
	Equal variances not assumed			6.379	24.156	0.000	9.58650	1.50288	6.54408	12.62892

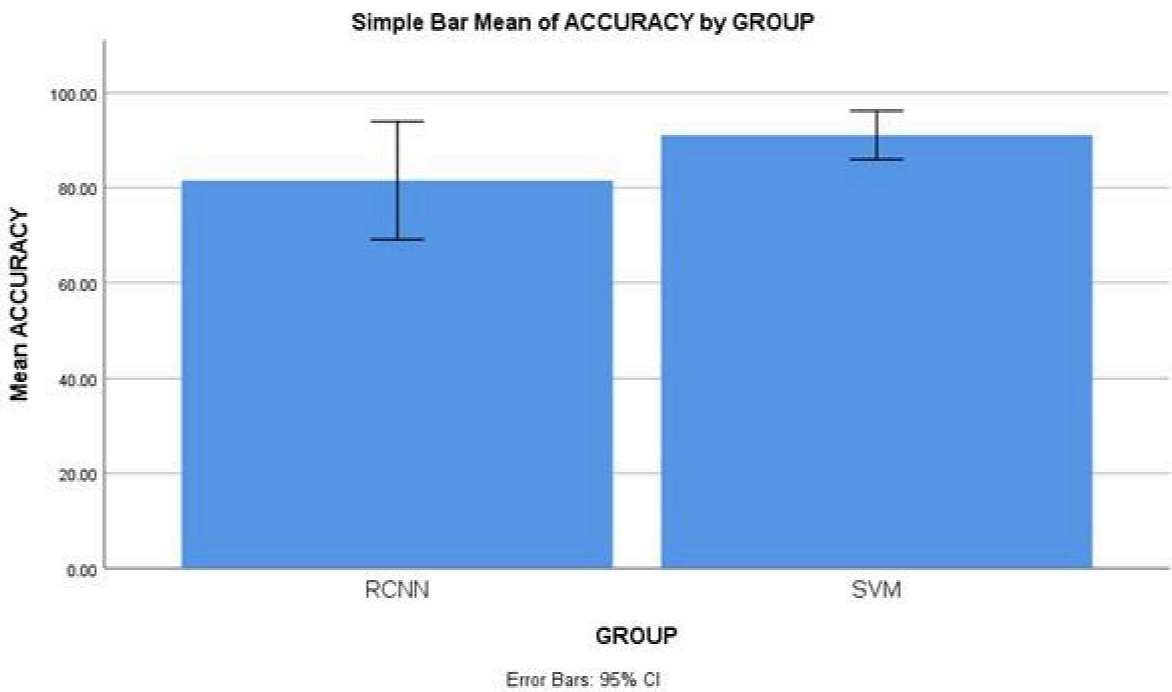

Figure 1 compares the SVM classifier's accuracy to that of the RCNN classifier. The SVM prediction model has a greater accuracy rate than the RCNN classification model, which has a rate of 81.52. The SVM classifier differs considerably from the RCNN classifier (test of independent samples, p 0.05). The SVM and RCNN accuracy rates are shown along the X-axis. Y-axis: Mean keyword identification accuracy, ±1 SD, with a 95% confidence interval.