**Title Page:**

Improving Accuracy of Prioritizing Emergency Cases in Hospitals Using Innovative Support Vector Machines (SVMs) Algorithm in Comparison with K-Nearest Neighbours

N.Mahesh1, Uma Priyadarsini2

N.Mahesh1

Research Scholar,

Department of Computer Science and Engineering,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, India, Pincode:-602105.

maheshmahesh1287.sse@saveetha.com

Uma Priyadarsini2

Research Guide, Corresponding Science and Engineering,

Department of Computer Science and Engineering,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, India, Pincode:602105.

umapriyadarsini@saveetha.com

**Keywords:** Emergency Cases, Prioritization, K-Nearest Neighbour, Research, Innovative Support Vector Machines, Machine Learning.

**ABSTRACT**

**Aim:**This study aims to create a resilient and dependable system for prioritizing emergency cases in hospitals by contrasting the effectiveness of the Innovative Support Vector Machines (SVMs) algorithm with the K-Nearest Neighbour approach.**Materials and** **Methods**:The prioritization of emergency cases in hospitals is explored by comparing the efficacy of Innovative Support Vector Machines and K-Nearest Neighbour algorithms, with a sample size of 30 in each of the two groups and a pretest analysis set at 80%. **Result:**The findings highlight a significant enhancement in the precision of prioritizing emergency cases using the SVM-based approach, achieving an accuracy rate of 94.37%, in contrast to the 53.03% accuracy obtained with the K-Nearest Neighbour algorithm. **Conclusion:**Within the realm of prioritizing emergency cases in hospitals, this study establishes that the SVM-based approach presents a notably more robust and accurate method when compared to K-Nearest Neighbour algorithms.

**Keywords:** Emergency Cases, Prioritization, K-Nearest Neighbour, Research, Support Vector Machines, Machine Learning.

# **INTRODUCTION**

Emergency case prioritization, commonly known as "triage," systematically evaluates and categorizes patients based on the severity and urgency of their medical conditions. This process facilitates efficient resource allocation by ensuring that the most critical cases receive immediate attention, while less severe cases are managed appropriately but with lower priority. The escalating strain on healthcare systems, coupled with increasing patient populations and a persistent demand for immediate care, underscores the imperative for innovative and robust prioritization systems [(“Survey-Based Calibration of a Parking Entry as a Single-Server Mathematical Queuing Model: A Case Study” 2020)](https://paperpile.com/c/foWXyE/27j8). Applications for prioritizing emergency cases in hospitals typically involve the utilization of triage systems, which categorize patients based on the severity of their condition and the urgency of their care needs. These applications often employ algorithms that take into account vital signs, symptoms, medical history, and available resources to allocate medical attention and resources efficiently to those in critical need, ensuring prompt delivery of lifesaving treatments [(Alipour Vaezi and Tavakkoli-Moghaddam 2020)](https://paperpile.com/c/foWXyE/BXsR). Furthermore, the integration of digital triage tools streamlines the process, empowering healthcare professionals to make rapid and informed decisions, ultimately enhancing patient outcomes in emergency situations.

The subject of hospital emergency cases has garnered attention in about 89 publications on Google Scholar and 53 research articles on IEEE Xplore [(“Safety Assessment of Drug Combinations Used in COVID-19 Treatment: In Silico Toxicogenomic Data-Mining Approach” 2020)](https://paperpile.com/c/foWXyE/M3aA). Research studies underscore the importance of implementing standardized protocols and algorithms that take into account factors like the severity of illness, available resources, and patient load to ensure effective prioritization of care. Furthermore, there is a growing exploration of emerging technologies, such as artificial intelligence and machine learning, aimed at improving the accuracy and efficiency of triage processes in emergency settings [(“Effect of Emergency Department Crowding on Outcomes of Admitted Patients” 2013)](https://paperpile.com/c/foWXyE/m4NH).

The primary objective of this study is to assess the impact of employing a purpose-built dataset on the accuracy of hospital emergency case prioritization [(“The Impact of ED Crowding on Early Interventions and Mortality in Patients with Severe Sepsis” 2017)](https://paperpile.com/c/foWXyE/ffhg). A comparative analysis demonstrates that the achieved accuracy surpasses that of the Logistic Regression algorithm. Departing from the conventional random forest algorithm, this research utilizes the Innovative Support Vector Machines algorithm with hyperparameter tuning, with the principal aim of enhancing the accuracy of forecasts for emergency cases in hospitals.

**MATERIALS AND METHODS**

Conducted within the Deep Learning Lab at Saveetha School of Engineering, this study is situated in the broader context of Saveetha Institute of Medical and Technical Sciences [(Gruen et al. 2006)](https://paperpile.com/c/foWXyE/0vot). The research entails grouping samples into two categories: Group 1 utilizes the Support Vector Machines Algorithm, whereas Group 2 employs the Logistic Regression Algorithm. Each group comprises 30 samples, with a sample estimation of 80% determined through the GPower Statistical Software test.

This research paper employs the patient priority dataset obtained from the open-access Kaggle platform, consisting of 6963 rows and encompassing 18 distinct attributes [(Rathore et al. 2009)](https://paperpile.com/c/foWXyE/81eG). The main emphasis is placed on utilizing specific attributes to improve the accuracy of predicting emergency analyses . Significantly, the analysis primarily depends on the 'need only' attribute as the sole text-dependent variable for classification and analytical purposes.

**K-Nearest Neighbour**

The k-Nearest Neighbors (k-NN) algorithm is a supervised machine learning method used for classification and regression tasks. In this algorithm, an object is classified by the majority vote of its k nearest neighbors, where the value of k represents the number of neighbors taken into consideration. The algorithm relies on the similarity of data points in feature space, making it a non-parametric and instance-based approach in machine learning.

**Pseudocode**

Step 1: Collect and Prepare Data.

X\_train = feature matrix for training data

y\_train = corresponding labels for training data

Step 2: Choose the K-Nearest Neighbour Parameters.

numberOfTrees = 100

numberOfFeaturesPerTree = sqrt(numberOfFeatures)

Step 3: Define K-Nearest Neighbour Model.

forest =K-NearestNeighbourAlgorithm(X\_train, y\_train, numberOfTrees, numberOfFeaturesPerTree)

Step 4: Train the K-Nearest Neighbour Model.

Step 5: Make Predictions.

X\_test = feature matrix for test data

predictions = K-Nearest NeighbourPredict(forest, X\_test)

Step 6: Evaluate Model Performance.

y\_test = corresponding labels for test data

accuracy = calculate\_accuracy(predictions, y\_test)

Step 7:Visualize Results.

**Innovative Support Vector Machine Algorithm**

Innovative Support Vector Machine is a powerful supervised learning technique that is widely utilized for regression and classification applications. By identifying the most effective hyperplane in the feature space to split different classes, it maximizes the margin between them. Innovative Support Vector Machines has proven to perform exceptionally well in a variety of fields, including image classification, bioinformatics, and finance. "A Practical Guide to Support Vector Classification." Its ability to handle high-dimensional data and nonlinear interactions makes it particularly suitable for complex datasets. Innovative Support Vector Machines ability to handle small sample sizes and resistance to overfitting make it a popular choice for real-world applications.

**Pseudocode**

Step 1: Collect and Prepare Data.

Assume X\_train is the feature matrix for training data, y\_train is the corresponding labels.

Step 2: Choose the Support Vector Machine Kernel.

Assume a 'linear' kernel for simplicity

Step 3: Define Support Vector Machine Model.

model = SVM(kernel='linear', C=1.0)

Step 4:Train the Support Vector Machine Model.

model.train(X\_train, y\_train)

Step 5: Make Predictions.

Assume X\_test is the feature matrix for test data.

predictions = model.predict(X\_test)

Step 6:Evaluate Model Performance.

You can use metrics like accuracy, precision, recall, and F1-score.

accuracy = calculate\_accuracy(predictions, y\_test)

Step 7:Visualize Results.

**Statistical Analysis**

SPSS, a statistical software tool, is employed for conducting statistical analyses on data derived from classifiers across various test sizes [(“Accuracy and Reliability of Emergency Department Triage Using the Emergency Severity Index: An International Multicenter Assessment” 2018)](https://paperpile.com/c/foWXyE/w4ic). Notably, the textual content within the testing dataset remains uninfluenced by the training dataset, establishing it as a distinct variable with heart-rate and blood pressure as dependent variables. In this context, the text component of the training dataset serves as an independent variable. The study involves a comparative assessment of the performance of the K-Nearest Neighbour and Innovative Support Vector Machine algorithms [(“Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index” 2018)](https://paperpile.com/c/foWXyE/JDKA). The outcomes from multiple iterations are leveraged for conducting an independent sample t-test to ascertain significant differences in performance.

**RESULT**

Innovative Support Vector Machines algorithms consistently exhibit a superior accuracy rate compared to K-Nearest Neighbour algorithms. To explore diverse accuracy rate variations, the experiment is iteratively conducted, allowing for the collection of comprehensive data. Subsequently, the gathered data undergoes statistical computations using the SPSS program to analyze the outcomes of the experiment. The statistical analysis includes the application of an independent sample t-test to assess any significant differences in performance between the two algorithms.

Table 1 provides a comprehensive overview of group statistics, showcasing the selected values and corresponding groups. The table contrasts the mean accuracy and standard deviation for Support Vector Machines Algorithms, revealing values of 94.37% and 1.847, respectively. Additionally, the standard error mean for the K-Nearest Neighbours Algorithm is calculated at .300, while the Support Vector Machines Algorithm records a slightly higher value of .337. Notably, the K-Nearest Neighbours method demonstrates an accuracy of 53.03%, while the Innovative Support Vector Machines approach outperforms with a significantly higher accuracy of 94.37%.

Table 2 highlights the application of SPSS computations to the Innovative Support Vector Machine Algorithm, followed by the implementation of an Independent Sample T-Test using sample collections. The significance level is set at (p=0.01, p<0.05), with a confidence interval of 95%. To compare the means of the two groups, a separate Sample t-test is employed. The accompanying bar graph visually juxtaposes the mean accuracy of the K-Nearest Neighbours algorithm (53.03) and the Support Vector Machine algorithm (94.37). Examining the mean accuracy individually for each algorithm reveals that the Innovative Support Vector Machine Algorithm consistently produces results with a lower standard deviation, indicating a higher level of consistency in its performance.

Figure 1 presents a comparative analysis of mean accuracy between K-Nearest Neighbours and Innovative Support Vector Machine algorithms through bar graphs. The y-axis represents mean accuracy, while the x-axis illustrates the algorithms, with error bars denoting the variability derived from both Innovative Support Vector Machine and K-Nearest Neighbours techniques. The error bars include the range of values within +/-2 standard deviations (SD) and a 95% confidence interval (CI), providing a visual depiction of the precision and confidence in the accuracy measurements for each algorithm.

**DISCUSSION**

Within this health prioritization research study, the Innovative Support Vector Machine algorithm consistently demonstrates higher accuracy compared to the K-Nearest Neighbours algorithm [(“An Electronic Emergency Triage System to Improve Patient Distribution by Critical Outcomes” 2016)](https://paperpile.com/c/foWXyE/qHBS). The independent samples t-test reveals a significantly greater level of significance for the Innovative Support Vector Machine technique (p=0.01, p<0.05). Specifically, the Innovative Support Vector Machine algorithm exhibits a mean accuracy of 94.37 with a standard deviation of 1.847, surpassing the K-Nearest Neighbours algorithm, which records a mean accuracy of 53.03 with a standard deviation of 1.614 [(Desautels et al. 2017)](https://paperpile.com/c/foWXyE/2L8k). The findings underscore the superior performance and reliability of the Innovative Support Vector Machine algorithm in the context of health prioritization.

To enhance the accuracy of health prioritization, a thorough comparison between the K-Nearest Neighbours and Innovative Support Vector Machine algorithms is imperative [(Hong, Haimovich, and Andrew Taylor 2018)](https://paperpile.com/c/foWXyE/Rwh6). K-Nearest Neighbours presents distinct advantages, particularly its efficiency in handling large, high-dimensional datasets [(Zhang et al. 2017)](https://paperpile.com/c/foWXyE/MJsG). Notably, the ensemble technique employed by K-Nearest Neighbours, involving the amalgamation of multiple decision trees and averaging their predictions, often results in superior generalization and robustness. This attribute holds significant value in the healthcare sector, given the inherent complexity and varied class distributions in datasets. In the realm of clinical practice, a thoughtful consideration of dataset characteristics, model interpretability, and computational constraints is essential when choosing between K-Nearest Neighbours and Innovative Support Vector Machine algorithms.There is no opposite findings in this research.

In the context of healthcare prioritization, a thorough comparison between Innovative Support Vector Machines and K-Nearest Neighbours underscores the importance of selecting the most suitable algorithm, considering dataset characteristics and clinical demands [(Moons et al. 2015)](https://paperpile.com/c/foWXyE/yVQj). Future research initiatives should concentrate on investigating hybrid methodologies that integrate the strengths of both algorithms to enhance diagnostic accuracy and enable personalized treatment strategies. While Innovative Support Vector Machines may offer superior accuracy and efficiency in specific scenarios, the theoretical underpinnings and support make it a preferred choice, particularly when model interpretability is crucial for healthcare practitioners in decision-making processes.

The innovative approach, integrating entropy with K-Nearest Neighbours, holds significant implications for clinical practice and represents a notable advancement in the application of machine learning in healthcare administration [(“Reporting and Interpreting Decision Curve Analysis: A Guide for Investigators” 2018)](https://paperpile.com/c/foWXyE/lZbX). The heightened accuracy of this methodology compared to older techniques, such as Innovative Support Vector Machine, has the potential to bring about improved patient outcomes in various healthcare conditions. This transformative aspect could lead to changes in early diagnosis and intervention procedures, showcasing the potential impact of this novel method on enhancing healthcare practices.

The experiment faces a key limitation stemming from the limited scope of features within the dataset, potentially restricting the accurate prediction of healthcare prioritization accuracy percentages [(Mirhaghi et al. 2015)](https://paperpile.com/c/foWXyE/d5sO). Enhancements in accuracy can be anticipated by incorporating additional independent and dependent factors into the analysis [(Europe, 2024.)](https://paperpile.com/c/foWXyE/uttX). Expanding the range of variables considered is essential for a more comprehensive understanding and improved predictive capabilities in healthcare prioritization.

Anticipated developments in hospital emergency services point towards a future characterized by technological advancements, shifts in healthcare delivery models, and a dedicated emphasis on enhancing efficiency and elevating patient outcomes.

**CONCLUSION**

In the proposed healthcare prioritization analysis framework, the Innovative Support Vector Machine Algorithm exhibits a remarkable accuracy of 94.37%, surpassing the K-Nearest Neighbours Algorithm, which achieves an accuracy of 53.03%. These results underscore the superior and statistically significant accuracy of the Innovative Support Vector Machine over the K-Nearest Neighbours Algorithm within the established framework.

**DECLARATION**

**Conflicts of interests**

No conflict of interest in this manuscript.

**Author contributions:**

Author NM was involved in data collection, data analysis and manuscript writing. Author UP was involved in conceptualization, data validation and critical review of manuscript writing.

**Acknowledgement**

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 providing the necessary infrastructure to carry out this work successfully.

**Funding**

We thank the following organizations for providing financial support that enabled us to complete the study.

1. Infoziant IT Solutions Pvt. Ltd., Chennai.

###### 2. Saveetha University.

3. Saveetha Institute of Medical And Technical Sciences.

4. Saveetha School of Engineering.

**REFERENCES**

[“Accuracy and Reliability of Emergency Department Triage Using the Emergency Severity Index: An International Multicenter Assessment.” 2018. *Annals of Emergency Medicine* 71 (5): 581–87.e3.](http://paperpile.com/b/foWXyE/w4ic)

[Alipour Vaezi, Mohammad, and Reza Tavakkoli-Moghaddam. 2020. “A New Methodology for COVID-19 Preparedness Centers Based on a Location-Allocation Platform.” *International Journal of Industrial and Systems Engineering* 13 (1): 35–41.](http://paperpile.com/b/foWXyE/BXsR)

[“An Electronic Emergency Triage System to Improve Patient Distribution by Critical Outcomes.” 2016. *The Journal of Emergency Medicine* 50 (6): 910–18.](http://paperpile.com/b/foWXyE/qHBS)

[Desautels, Thomas, Ritankar Das, Jacob Calvert, Monica Trivedi, Charlotte Summers, David J. Wales, and Ari Ercole. 2017. “Prediction of Early Unplanned Intensive Care Unit Readmission in a UK Tertiary Care Hospital: A Cross-Sectional Machine Learning Approach.” *BMJ Open* 7 (9): e017199.](http://paperpile.com/b/foWXyE/2L8k)

[“Effect of Emergency Department Crowding on Outcomes of Admitted Patients.” 2013. *Annals of Emergency Medicine* 61 (6): 605–11.e6.](http://paperpile.com/b/foWXyE/m4NH)

[Europe, P. M. C. 2024. “Europe PMC.” Accessed March 7, 2024.](http://paperpile.com/b/foWXyE/uttX) <https://europepmc.org/article/med/3928249?utm_campaign=share&utm_medium=email&utm_source=email_share_mailer&client=bot&client=bot>[.](http://paperpile.com/b/foWXyE/uttX)

[Gruen, Russell L., Gregory J. Jurkovich, Lisa K. McIntyre, Hugh M. Foy, and Ronald V. Maier. 2006. “Patterns of Errors Contributing to Trauma Mortality: Lessons Learned From 2594 Deaths.” *Annals of Surgery* 244 (3): 371.](http://paperpile.com/b/foWXyE/0vot)

[Hong, Woo Suk, Adrian Daniel Haimovich, and R. Andrew Taylor. 2018. “Predicting Hospital Admission at Emergency Department Triage Using Machine Learning.” *PloS One* 13 (7): e0201016.](http://paperpile.com/b/foWXyE/Rwh6)

[“Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index.” 2018. *Annals of Emergency Medicine* 71 (5): 565–74.e2.](http://paperpile.com/b/foWXyE/JDKA)

[Mirhaghi, Amir, Hadi Kooshiar, Habibollah Esmaeili, and Mohsen Ebrahimi. 2015. “Outcomes for Emergency Severity Index Triage Implementation in the Emergency Department.” *Journal of Clinical and Diagnostic Research: JCDR* 9 (4): OC04.](http://paperpile.com/b/foWXyE/d5sO)

[Moons, Karel G. M., Douglas G. Altman, Johannes B. Reitsma, John P. A. Ioannidis, Petra Macaskill, Ewout W. Steyerberg, Andrew J. Vickers, David F. Ransohoff, and Gary S. Collins. 2015. “Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis Or Diagnosis (TRIPOD): Explanation and Elaboration.” *Annals of Internal Medicine*, January. https://doi.org/](http://paperpile.com/b/foWXyE/yVQj)[10.7326/M14-0698](http://dx.doi.org/10.7326/M14-0698)[.](http://paperpile.com/b/foWXyE/yVQj)

[Rathore, Saif S., Jeptha P. Curtis, Jersey Chen, Yongfei Wang, Brahmajee K. Nallamothu, Andrew J. Epstein, and Harlan M. Krumholz. 2009. “Association of Door-to-Balloon Time and Mortality in Patients Admitted to Hospital with ST Elevation Myocardial Infarction: National Cohort Study.” *BMJ*  338 (May). https://doi.org/](http://paperpile.com/b/foWXyE/81eG)[10.1136/bmj.b1807](http://dx.doi.org/10.1136/bmj.b1807)[.](http://paperpile.com/b/foWXyE/81eG)

[“Reporting and Interpreting Decision Curve Analysis: A Guide for Investigators.” 2018. *European Urology* 74 (6): 796–804.](http://paperpile.com/b/foWXyE/lZbX)

[“Safety Assessment of Drug Combinations Used in COVID-19 Treatment: In Silico Toxicogenomic Data-Mining Approach.” 2020. *Toxicology and Applied Pharmacology* 406 (November): 115237.](http://paperpile.com/b/foWXyE/M3aA)

[“Survey-Based Calibration of a Parking Entry as a Single-Server Mathematical Queuing Model: A Case Study.” 2020. *Alexandria Engineering Journal* 59 (2): 829–38.](http://paperpile.com/b/foWXyE/27j8)

[“The Impact of ED Crowding on Early Interventions and Mortality in Patients with Severe Sepsis.” 2017. *The American Journal of Emergency Medicine* 35 (7): 953–60.](http://paperpile.com/b/foWXyE/ffhg)

[Zhang, Xingyu, Joyce Kim, Rachel E. Patzer, Stephen R. Pitts, Aaron Patzer, and Justin D. Schrager. 2017. “Prediction of Emergency Department Hospital Admission Based on Natural Language Processing and Neural Networks.” *Methods of Information in Medicine* 56 (05): 377–89.](http://paperpile.com/b/foWXyE/MJsG)

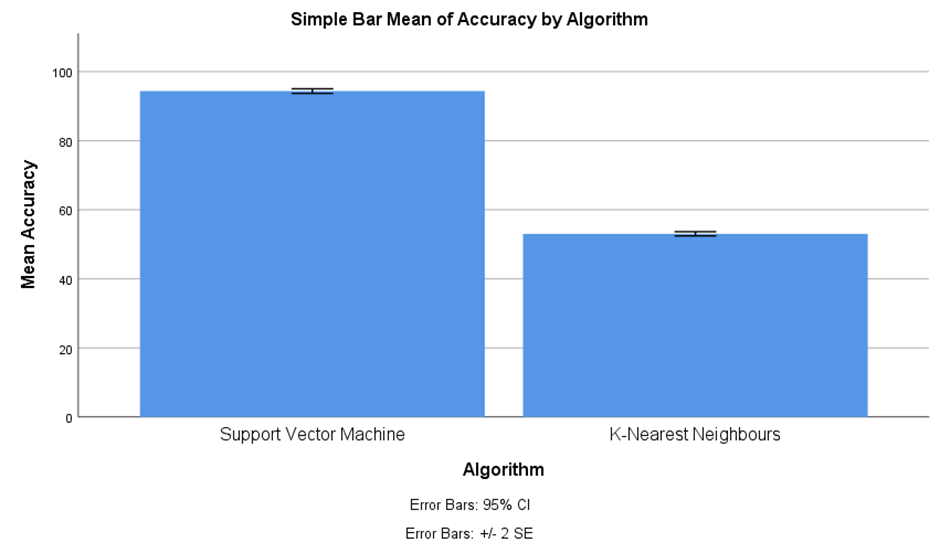
**TABLES AND FIGURES**

**Table 1.**The Innovative Support Vector Machine demonstrates a mean value of 94.37, significantly outperforming the K-Nearest Neighbours with its mean value of 53.03. Correspondingly, the standard deviations for these algorithms are 1.847 and 1.614, respectively. These metrics highlight the substantial difference in performance and variability between the two algorithms.

|  | **Algorithm** | **N** | **Mean** | **Std.Deviation** | **Std.Error Mean** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | **Support Vector Machine** | 30 | 94.37 | 1.847 | .337 |
| **K-Nearest Neighbours** | 29 | 53.03 | 1.614 | .300 |

**Table 2.** As the error diminishes in independent sample testing, there is a concurrent increase in accuracy. The statistical significance of this association is underscored by a two-tailed significance level of less than 0.001 (p<0.05), affirming the robustness of the observed relationship.

|  | **Leven’s test for equality of Variances** | | **T-test for equality of means** | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **f** | **Sig** | **t** | **dif** | **sig(2-tailed)** | **Mean.diff** | **Std.Error difference** | **95% confidence interval of the difference** | |
| **Lower** | **Uppe**r |
| **Equal variances assumed** | .848 | .361 | 91.386 | 57 | .000 | 41.332 | .452 | 40.427 | 42.238 |
| **Equal variances not assumed** |  |  | 91.598 | 56.438 | .000 | 41.332 | .451 | 40.428 | 42.236 |



**Fig. 1.**The Innovative Support Vector Machine Algorithm exhibits superior performance compared to the K-Nearest Neighbours Algorithm, achieving an accuracy of 94.37% versus 53.03%, accompanied by a marginally higher standard deviation. This contrast is visually represented in a graph, where the X-axis denotes Innovative Support Vector Machine and K-Nearest Neighbours Algorithms, while the Y-axis illustrates mean size and accuracy, incorporating a range of ±2 standard errors.