**Title Page:**

Prioritization of Emergency Cases in Hospitals Using Innovative Support Vector Machines (SVMs) Algorithm Compared with Logistic Regression for Improving Accuracy

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, Logistic Regression, Research, Innovative Support Vector Machines, Machine Learning.

**ABSTRACT**

**Aim:**The objective of this study is to establish a resilient and dependable system for prioritizing emergency cases within hospital settings, utilizing the Innovative Support Vector Machines (SVMs) algorithm as a point of comparison with logistic regression. This research aims to assess the effectiveness and performance of Innovative SVMs in contrast to Logistic Regression for enhanced accuracy in prioritizing emergency cases. **Materials and Methods**: In the context of prioritizing emergency cases in hospitals, this study employs Innovative Support Vector Machines and compares their effectiveness with Logistic Regression. The research involves two groups with a sample size of 30 each, alongside a pretest analysis indicating an 80% baseline accuracy. **Result:** The findings demonstrate a significant enhancement in the precision of prioritizing emergency cases through the implementation of the Innovative SVM-based approach, yielding an accuracy rate of 93.87%. In contrast, the logistic regression algorithm achieved a lower accuracy of 63.80%. **Conclusion:** Within the realm of prioritizing emergency cases in hospital settings, this study underscores that the SVM-based approach emerges as notably more robust and accurate when juxtaposed with logistic regression algorithms. The research findings highlight the superiority of the SVM-based method in providing enhanced precision for prioritization in emergency scenarios.

**Keywords:** Emergency Cases, Prioritization, Logistic Regression, Research, Innovative Support Vector Machines, Machine Learning.

# **INTRODUCTION**

Prioritizing emergency cases systematically is also known as "triage," and it involves classifying patients according to the seriousness and urgency of their medical conditions [(Song et al., 2024.)](https://paperpile.com/c/9M4PAA/gElg). By classifying patients, healthcare professionals can more effectively distribute their limited resources, giving the most urgent cases prompt attention while managing less serious situations with less urgency [(Stamford, Schmidt, and Friedl, 2024.)](https://paperpile.com/c/9M4PAA/Aw7Z). Referred to as "triage," emergency case prioritizing is the methodical process of assessing and classifying patients according to the seriousness and urgency of their medical issues. In addition, the need for creative and reliable prioritization systems is driven by the growing burden on healthcare systems, the expansion of patient populations, and the constant need for urgent care.Hospitals utilize triage systems, which classify patients according to the severity of their conditions and the urgency of their need for care, to prioritize emergency cases [(Besaleva and Weaver, 2024.)](https://paperpile.com/c/9M4PAA/dShk). In order to efficiently allocate medical attention and resources to individuals in the greatest need and guarantee that life-saving treatment is provided as soon as possible, these programs may make use of algorithms that take into account vital signs, symptoms, medical histories, and available resources. Additionally, by streamlining the procedure and empowering medical personnel to act quickly and intelligently, digital triage systems might eventually improve patient outcomes in emergency scenarios.

Hospital emergency cases have garnered attention in around 89 publications on Google Scholar and 53 research articles on IEEE Xplore. These studies underscore the importance of establishing standardized protocols and algorithms that account for factors such as illness severity, resource availability, and patient load to ensure effective prioritization of care. Furthermore, there is a growing exploration of emerging technologies like artificial intelligence and machine learning to boost the precision and efficiency of triage processes in emergency settings [(Islamaj Doğan et al. 2019)](https://paperpile.com/c/9M4PAA/bAyC).

The objective of this study is to assess whether the utilization of a purpose-built dataset enhances the accuracy of hospital emergency case prioritization [(Alsheikh et al., 2024.)](https://paperpile.com/c/9M4PAA/kQdY). Comparative analysis indicates that the achieved accuracy surpasses that of the logistic regression algorithm. Departing from the conventional random forest algorithm, this research employs the Innovative Support Vector Machine algorithm with hyperparameter tuning, aiming primarily to enhance 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 within the broader framework of Saveetha Institute of Medical and Technical Sciences [(Shoaib, Jha, and Verma, 2024.)](https://paperpile.com/c/9M4PAA/H2hN). The research entails the classification of samples into two groups: Group 1 employs the Innovative Support Vector Machines Algorithm, and Group 2 utilizes 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 utilizes a dataset sourced from the patient priority dataset, acquired through the open-access Kaggle platform, consisting of 6963 rows and encompassing 18 distinct attributes [(Ben said et al., 2024)](https://paperpile.com/c/9M4PAA/9J6Z). The central emphasis of the study revolves around harnessing specific attributes to improve the precision of predicting emergency analyses. Significantly, the analysis predominantly depends on the 'need only' attribute as the exclusive text-dependent variable for classification and analytical purposes.

**Logistic Regression Algorithm**

Logistic Regression is a statistical method used for binary classification, predicting the probability of an event occurring based on one or more independent variables. It is particularly suited for scenarios where the outcome variable is categorical and has two possible outcomes. The model employs the logistic function to transform a linear combination of input features into a probability score, facilitating the classification of instances into one of the two categories.

**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 Logistic Regression Parameters.

numberOfTrees = 100

numberOfFeaturesPerTree = sqrt(numberOfFeatures)

Step 3: Define Logistic Regression Model.

forest = LogisticRegressionAlgorithm(X\_train, y\_train, numberOfTrees, numberOfFeaturesPerTree)

Step 4: Train the Logistic Regression Model.

Step 5: Make Predictions.

X\_test = feature matrix for test data

predictions = Logistic RegressionPredict(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 Innovative 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 Innovative Support Vector Machine Kernel.

Assume a 'linear' kernel for simplicity

Step 3: Define Innovative Support Vector Machine Model.

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

Step 4:Train theInnovative 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**

Statistical computations for data obtained from classifiers at various test sizes are conducted using the SPSS tool [(Shahzad and Kim, 2024.)](https://paperpile.com/c/9M4PAA/uWYp). The testing dataset's text portion is independent of the training dataset, where the text segment of the training dataset serves as the independent variable with heart-rate and blood pressure as dependent variables. A comparative analysis of the performance of Logistic Regression and Innovative Support Vector Machine algorithms is carried out, and the results from multiple iterations are utilized for an independent sample t-test.

**RESULT**

Innovative Support Vector Machines algorithms exhibit a superior accuracy rate compared to Logistic Regression algorithms. The experiment involves multiple repetitions to ascertain diverse accuracy rate scales before consolidating the data. Additionally, statistical computations, utilizing the SPSS program, are conducted on the experiment's outcomes, followed by the execution of an independent sample t-test.

Table 1 provides the group statistics, presenting the selected number of values and groups. In this table, the mean accuracy and standard deviation for Innovative Support Vector Machines Algorithms are contrasted, indicating values of 93.87% and 1.871, respectively. The standard error mean for the Logistic Regression Algorithm is .334, while for the Innovative Support Vector Machines Algorithm, it is .342, corresponding to accuracies of 63.80% and 93.87%, respectively. Notably, the Innovative Support Vector Machines approach demonstrates a higher accuracy compared to the Logistic Regression method.

Table 2 displays the application of SPSS computations to the Innovative Support Vector Machine Algorithm, followed by the utilization of an Independent Sample T-Test on the sample collections. The significance level is set at (p=0.01, p<0.05), with a confidence interval of 95%. Additionally, a separate Sample t-test is employed to compare the means of the two groups. The accompanying bar graph illustrates the mean accuracy of the Logistic Regression algorithm (83.16) and the Innovative Support Vector Machine algorithm (94.10). A closer examination of each algorithm's mean accuracy reveals that the Innovative Support Vector Machine Algorithm consistently produces results with a lower standard deviation.

Figure 1 presents a comparative analysis of mean accuracy through bar graphs for Logistic Regression and Innovative Support Vector Machine algorithms. The y-axis depicts mean accuracy, while the x-axis represents the algorithms, featuring error bars denoting the Innovative Support Vector Machine and Logistic Regression techniques, inclusive of their +/-2 SD and 95% CI.

**DISCUSSION**

In this health prioritization research, the Logistic Regression algorithm exhibits lower accuracy compared to the Innovative Support Vector Machine. Utilizing an independent sample t-test, the Innovative Support Vector Machine technique demonstrates higher significance (p=0.01, p<0.05). The mean accuracy for the Innovative Support Vector Machine algorithm is 93.87 with a standard deviation of 1.871, while for Logistic Regression, it is 63.80 with a standard deviation of 1.827 [(“Fall Detection in Older Adults with Mobile IoT Devices and Machine Learning in the Cloud and on the Edge” 2020)](https://paperpile.com/c/9M4PAA/wMYc).

Evaluating the Logistic Regression and Innovative Support Vector Machine algorithms is essential to enhance the accuracy of health prioritization. Logistic Regression offers various advantages over Innovative Support Vector Machine, particularly in its effective processing of large, high-dimensional datasets [(“A Novel Approach of Telemedicine for Managing Fetal Condition Based on Machine Learning Technology from IoT-Based Wearable Medical Device” 2021)](https://paperpile.com/c/9M4PAA/a930). The implementation of Logistic Regression ensemble techniques, which involve combining multiple decision trees and averaging their predictions, often results in improved generalization and robustness. Given the intricacies of healthcare datasets with complex patterns and varying class distributions, careful consideration of dataset characteristics, model interpretability, and computing constraints is imperative when choosing between Logistic Regression and Innovative Support Vector Machine in clinical practice.There is no opposite findings in this research.

The comparison between Innovative Support Vector Machines and Logistic Regression for healthcare prioritization underscores the importance of choosing the most suitable algorithm according to dataset characteristics and clinical needs [(Pavel et al., 2024)](https://paperpile.com/c/9M4PAA/VNj3). Future research efforts should concentrate on investigating hybrid approaches that harness the strengths of both algorithms, enhancing diagnostic accuracy and enabling customized treatment strategies. While Innovative Support Vector Machine may excel in accuracy and efficiency in specific situations, its theoretical underpinnings and support make it a preferred alternative, particularly when model transparency is essential for healthcare practitioners in decision-making processes.

The Innovative approach, integrating entropy with Logistic Regression, holds significant implications for clinical practice and represents a notable advancement in machine learning applications within healthcare administration [(Mathur et al., 2024)](https://paperpile.com/c/9M4PAA/PZgQ). The methodology's enhanced accuracy, surpassing older techniques such as Innovative Support Vector Machine, has the potential to positively impact patient outcomes in various healthcare conditions. This shift in accuracy may bring about changes in early diagnosis and intervention procedures, contributing to more effective healthcare practices.

The experiment faces a limitation in the form of a restricted set of features within the dataset, potentially limiting the accuracy of predicting healthcare prioritization percentages [(Monkaresi, Calvo, and Yan, 2024.)](https://paperpile.com/c/9M4PAA/kUUe). The enhancement of accuracy is anticipated through the incorporation of additional independent and dependent factors.

The future outlook for healthcare emergencies within hospitals is poised for evolution, driven by technological advancements, shifts in healthcare delivery models, and a dedicated emphasis on enhancing efficiency and optimizing patient outcomes.

**CONCLUSION**

In the suggested framework for healthcare prioritization analysis, the Innovative Support Vector Machine Algorithm demonstrates an accuracy of 93.87%, surpassing the Logistic Regression Algorithm, which achieves 63.80% accuracy. This substantiates the assertion that the proposed framework establishes the superior and statistically significant accuracy of the Innovative Support Vector Machine over the Logistic Regression Algorithm.

**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**

[Alsheikh, Mohammad Abu, Dinh Thai Hoang, Dusit Niyato, Hwee-Pink Tan, and Shaowei Lin. 2024. “Markov Decision Processes With Applications in Wireless Sensor Networks: A Survey.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/kQdY) <https://ieeexplore.ieee.org/abstract/document/7080987/>[.](http://paperpile.com/b/9M4PAA/kQdY)

[“A Research Approach of Telemedicine for Managing Fetal Condition Based on Machine Learning Technology from IoT-Based Wearable Medical Device.” 2021. In *Machine Learning and the Internet of Medical Things in Healthcare*, 113–34. Academic Press.](http://paperpile.com/b/9M4PAA/a930)

[Ben said, Ahmed, Mohamed Fathi Al-Sa’D, Mounira Tlili, Alaa Awad Abdellatif, Amr Mohamed, Tarek Elfouly, Khaled Harras, and Mark Dennis O’Connor. 2024. “A Deep Learning Approach for Vital Signs Compression and Energy Efficient Delivery in Mhealth Systems.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/9J6Z) <https://ieeexplore.ieee.org/abstract/document/8372913/>[.](http://paperpile.com/b/9M4PAA/9J6Z)

[Besaleva, Liliya I., and Alfred C. Weaver. 2024. “Applications of Social Networks and Crowdsourcing for Disaster Management Improvement.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/dShk) <https://ieeexplore.ieee.org/abstract/document/6693335/>[.](http://paperpile.com/b/9M4PAA/dShk)

[“Fall Detection in Older Adults with Mobile IoT Devices and Machine Learning in the Cloud and on the Edge.” 2020. *Information Sciences* 537 (October): 132–47.](http://paperpile.com/b/9M4PAA/wMYc)

[Islamaj Doğan, Rezarta, Sun Kim, Andrew Chatr-aryamontri, Chih-Hsuan Wei, Donald C. Comeau, Rui Antunes, Sérgio Matos, et al. 2019. “Overview of the BioCreative VI Precision Medicine Track: Mining Protein Interactions and Mutations for Precision Medicine.” *Database: The Journal of Biological Databases and Curation* 2019 (January): bay147.](http://paperpile.com/b/9M4PAA/bAyC)

[Mathur, Neha, Greig Paul, James Irvine, Mohamed Abuhelala, Arjan Buis, and Ivan Glesk. 2024. “A Practical Design and Implementation of a Low Cost Platform for Remote Monitoring of Lower Limb Health of Amputees in the Developing World.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/PZgQ) <https://ieeexplore.ieee.org/abstract/document/7723857/>[.](http://paperpile.com/b/9M4PAA/PZgQ)

[Monkaresi, Hamed, Rafael A. Calvo, and Hong Yan. 2024. “A Machine Learning Approach to Improve Contactless Heart Rate Monitoring Using a Webcam.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/kUUe) <https://ieeexplore.ieee.org/abstract/document/6671395/>[.](http://paperpile.com/b/9M4PAA/kUUe)

[Pavel, Misha, Holly B. Jimison, Ilkka Korhonen, Christine M. Gordon, and Niilo Saranummi. 2024. “Behavioral Informatics and Computational Modeling in Support of Proactive Health Management and Care.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/VNj3) <https://ieeexplore.ieee.org/abstract/document/7283558/>[.](http://paperpile.com/b/9M4PAA/VNj3)

[Shahzad, Ahsan, and Kiseon Kim. 2024. “FallDroid: An Automated Smart-Phone-Based Fall Detection System Using Multiple Kernel Learning.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/uWYp) <https://ieeexplore.ieee.org/abstract/document/8362961/>[.](http://paperpile.com/b/9M4PAA/uWYp)

[Shoaib, Mohammed, Niraj K. Jha, and Naveen Verma. 2024. “Algorithm-Driven Architectural Design Space Exploration of Domain-Specific Medical-Sensor Processors.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/H2hN) <https://ieeexplore.ieee.org/abstract/document/6338362/>[.](http://paperpile.com/b/9M4PAA/H2hN)

[Song, Lei, Yongcai Wang, Ji-Jiang Yang, and Jianqiang Li. 2024. “Health Sensing by Wearable Sensors and Mobile Phones: A Survey.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/gElg) <https://ieeexplore.ieee.org/abstract/document/7001885/>[.](http://paperpile.com/b/9M4PAA/gElg)

[Stamford, Jonathan A., Peter N. Schmidt, and Karl E. Friedl. 2024. “What Engineering Technology Could Do for Quality of Life in Parkinson’s Disease: A Review of Current Needs and Opportunities.” Accessed March 7, 2024.](http://paperpile.com/b/9M4PAA/Aw7Z) <https://ieeexplore.ieee.org/abstract/document/7177045/>[.](http://paperpile.com/b/9M4PAA/Aw7Z)

Alsheikh, Mohammad Abu, Dinh Thai Hoang, Dusit Niyato, Hwee-Pink Tan, and Shaowei Lin. 2024. “Markov Decision Processes With Applications in Wireless Sensor Networks: A Survey.” Accessed March 7, 2024. https://ieeexplore.ieee.org/abstract/document/7080987/.

Besaleva, Liliya I., and Alfred C. Weaver. 2024. “Applications of Social Networks and Crowdsourcing for Disaster Management Improvement.” Accessed March 7, 2024. https://ieeexplore.ieee.org/abstract/document/6693335/.

Song, Lei, Yongcai Wang, Ji-Jiang Yang, and Jianqiang Li. 2024. “Health Sensing by Wearable Sensors and Mobile Phones: A Survey.” Accessed March 7, 2024. https://ieeexplore.ieee.org/abstract/document/7001885/.

Stamford, Jonathan A., Peter N. Schmidt, and Karl E. Friedl. 2024. “What Engineering Technology Could Do for Quality of Life in Parkinson’s Disease: A Review of Current Needs and Opportunities.” Accessed March 7, 2024. https://ieeexplore.ieee.org/abstract/document/7177045/.

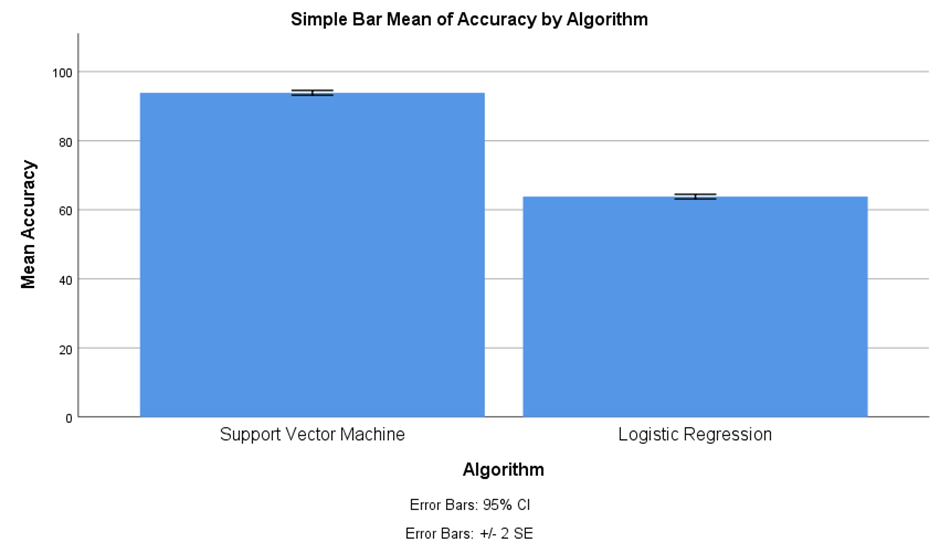
**TABLES AND FIGURES**

**Table 1.** The Innovative Support Vector Machine demonstrates a mean value of 93.87, surpassing Logistic Regression with its mean value of 63.80. The standard deviations for these algorithms are 1.871 and 1.827, respectively. These metrics highlight the notable distinctions in both central tendency and variability between the two algorithms.

|  | **Algorithm** | **N** | **Mean** | **Std.Deviation** | **Std.Error Mean** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | **Support Vector Machine** | 30 | 93.87 | 1.871 | .342 |
| **Logistic Regression** | 30 | 63.80 | 1.827 | .334 |

**Table 2.** The accuracy rises as the error decreases in independent sample testing. The two tailed significance ,falling below 0.001 (p<0.05), shows the statistical significance of this 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** | .207 | .651 | 62.683 | 58 | .000 | 30.067 | .477 | 29.111 | 31.022 |
| **Equal variances not assumed** |  |  | 62.83 | 57.968 | .000 | 30.067 | .477 | 29.111 | 31.022 |



**Fig. 1.** The Innovative Support Vector Machine Algorithm outperforms the Logistic Regression Algorithm with 93.87% versus 63.80% accuracy, and slightly superior standard deviation. The comparison is depicted on the graph, with the X-axis representing Innovative Support Vector Machine and Logistic Regression Algorithms and the Y axis reflecting mean size and accuracy with a range of ±2 standard errors.