**Title Page:**

Prioritizing Emergency Cases in Hospitals using Innovative Support Vector Machines Algorithm Comparing with Random Forest Algorithm for Better Accuracy

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**Keywords:** Emergency Cases, Prioritization, Random Forest, Research, Innovative Support Vector Machines, Machine Learning.

**ABSTRACT**

**Aim:** The aim of this study is to develop a robust and reliable system for prioritizing emergency cases in hospitals using the Innovative Support Vector Machines (SVMs) algorithm compared with random forest. **Materials and Methods**: Prioritizing emergency cases in hospitals using support vector machines compared with Random Forest, the sample size of two groups is 30 and pretest analysis of 80%. **Result:** The results reveal a notable improvement in the accuracy of prioritizing emergency cases with the SVM-based approach, achieving an accuracy rate of 94.10%, compared to 83.16% for Random Forest algorithm. **Conclusion:** In the context of prioritizing emergency cases in hospitals, this research demonstrates that the Innovative SVM-based approach offers a significantly more robust and accurate method compared to Random Forest algorithms.

**Keywords:** Emergency Cases, Prioritization, Random Forest, Research, Innovative Support Vector Machines, Machine Learning.

# **INTRODUCTION**

Emergency case prioritization, often referred to as "triage," is the systematic process of evaluating and categorizing patients based on the severity and urgency of their medical conditions [(“Prioritizing and Queueing the Emergency Departments’ Patients Using a Novel Data-Driven Decision-Making Methodology, a Real Case Study” 2022)](https://paperpile.com/c/taS6yc/UmIs). This categorization enables healthcare providers to allocate resources efficiently, ensuring that the most critical cases receive immediate attention, while less severe cases are managed appropriately but with less immediate priority [(Shin and Lee 2020)](https://paperpile.com/c/taS6yc/lCm5). Emergency case prioritization, often referred to as "triage," is the systematic process of evaluating and categorizing patients based on the severity and urgency of their medical conditions. Furthermore, the increased strain on healthcare systems, growing patient populations, and the perpetual demand for immediate care necessitate the development of innovative and robust prioritization systems [(Elalouf and Wachtel 2021)](https://paperpile.com/c/taS6yc/p3Z5). Applications for prioritizing emergency cases in hospitals typically involve the use of triage systems, which categorize patients based on the severity of their condition and the urgency of their need for care. These applications may utilize algorithms that consider vital signs, symptoms, medical history, and available resources to efficiently allocate medical attention and resources to those in most critical need, ensuring that lifesaving treatment is delivered promptly [(Huang, Yuan, and Ephremides, 2024.)](https://paperpile.com/c/taS6yc/av9a). Additionally, digital triage tools can streamline the process, enabling healthcare professionals to make rapid and informed decisions, ultimately improving patient outcomes in emergency situations.

The research of hospital emergency cases is covered in approximately 89 publications on Google Scholar and 53 research articles on IEEE Xplore.Studies emphasize the need for standardized protocols and algorithms that consider factors such as severity of illness, available resources, and patient load to prioritize care effectively [(“Reducing Waiting Time for Remote Patients in Telemedicine with Considering Treated Patients in Emergency Department Based on Body Sensors Technologies and Hybrid Computational Algorithms: Toward Scalable and Efficient Real Time Healthcare Monitoring System” 2020)](https://paperpile.com/c/taS6yc/WdX1). Additionally, emerging technologies like artificial intelligence and machine learning are increasingly being explored to enhance the accuracy and efficiency of triage processes in emergency settings.

The goal of the current study is to determine whether using a dataset created especially for this reason can improve the accuracy of hospital emergency case prioritization [(Salman et al. 2014)](https://paperpile.com/c/taS6yc/Aw4O). A comparison shows that the accuracy obtained is higher than that of the Random Forest algorithm. Instead of using the traditional random forest algorithm, the Innovative Support Vector Machine algorithm with hyperparameter tuning is applied in this study with the primary goal of improving the accuracy of Emergency cases in Hospital forecasts.

**MATERIALS AND METHODS**

The proposed research is conducted in the Deep Learning Lab at Saveetha School of Engineering, within the larger context of Saveetha Institute of Medical and Technical Sciences . It involves the categorization of samples into two groups: Group 1 utilizes the Innovative Support Vector Machines Algorithm, while Group 2 employs the Random Forest Algorithm. Each group consists of 30 samples, with a sample estimation of 80% determined using the GPower Statistical Software test[(Kalid et al. 2018)](https://paperpile.com/c/taS6yc/UWgd).

The dataset utilized in this paper is sourced from the patient priority dataset, obtained from the open-access Kaggle platform. It comprises 6963 rows and includes 18 distinct attributes [(“Current Application of Digital Diagnosing Systems for Retinopathy of Prematurity” 2021)](https://paperpile.com/c/taS6yc/hv1C). The primary focus lies on leveraging specific attributes to enhance the accuracy of emergency analysis prediction. Notably, the analysis predominantly relies on the 'need only' attribute as the sole text-dependent variable for classification and analysis purposes.

**Random Forest Algorithm**

The Random Forest algorithm, when applied to emergency cases in hospitals, is a machine learning technique designed to aid in the classification and prioritization of patients based on the severity of their condition and the urgency of medical intervention required. It leverages an ensemble learning approach, combining multiple decision trees to make predictions regarding patient outcomes and resource allocation. By aggregating the predictions of individual trees, Random Forest can provide more robust and accurate assessments of patient priority, ultimately improving the efficiency and effectiveness of emergency medical care delivery.

**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 Random Forest Parameters.

numberOfTrees = 100

numberOfFeaturesPerTree = sqrt(numberOfFeatures)

Step 3: Define Random Forest Model.

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

Step 4: Train the Random Forest Model.

Step 5: Make Predictions.

X\_test = feature matrix for test data

predictions = RandomForestPredict(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 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 the Innovative 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.

Use metrics like accuracy, precision, recall, and F1-score.

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

Step 7:Visualize Results.

**Statistical Analysis**

A statistical program called SPSS tool is used to do statistical computations for the data obtained from classifiers at different test sizes [(“Triage in Medicine, Part I: Concept, History, and Types” 2007)](https://paperpile.com/c/taS6yc/rUiz). While the text portion of the testing dataset is independent of the training dataset, the text portion of the training dataset is an independent variable [(“Task Offloading in Edge Computing for Machine Learning-Based Smart Healthcare” 2021)](https://paperpile.com/c/taS6yc/djAH) with heart-rate and blood pressure as dependent variables. The Random Forest and Innovative Support Vector Machine algorithms' respective performances are compared. The results of the iterations' data were used to conduct an independent sample t-test.

**RESULT**

The accuracy rate of Support Vector Machines algorithms is higher than that of Random Forest algorithms. In order to determine various accuracy rate scales, the experiment is repeated several times before the data are gathered. furthermore carried out the statistical computations utilizing the SPSS program and the experiment's outcomes. The t-test for independent samples is run.

In table 1, it presents the group statistics table, which indicates the number of values and groups that have been selected. The mean accuracy and standard deviation for Innovative Support Vector Machines Algorithms 94.10% and 2.084 are contrasted in this table. The standard error mean for the Random Forest Algorithm (.341) and Innovative Support Vector Machines Algorithm (.380) are 83.16% and 1.865, respectively. It is found that the Random Forest method has an accuracy of 83.16%, whereas the Innovative Support Vector Machines approach has a higher accuracy of 94.10%.

In table 2, it shows that, after applying the SPSS computations to the Innovative Support Vector Machine Algorithm, the Independent Sample T-Test is used with the sample collections, setting the level of significance as (p=0.01, p<0.05) with the confidence interval 95%. A separate Sample t-test is used to compare the means of the two groups.The bar graph compares the mean accuracy of the Random Forest algorithm and the Support Vector Machine algorithm, which are 83.16 and 94.10, respectively. Let us look at the mean accuracy of each algorithm separately. Results with a lower standard deviation seem to be produced more consistently by the Support Vector Machine Algorithm.

Figure 1, compares the mean accuracy of Random Forest and Innovative Support Vector Machine bar graphs. The y-axis displays mean accuracy, and the x-axis displays algorithms which have error bars from the Innovative Support Vector Machine and Random Forest techniques, along with their +/-2 SD and 95% CI.

**DISCUSSION**

In this research study on health prioritizing, the Random Forest algorithm is roughly less accurate than the Innovative Support Vector Machine [(Kalid et al. 2017)](https://paperpile.com/c/taS6yc/TJmV). Using the independent samples t-test, the Innovative Support Vector Machine technique yields greater significance (p=0.01, p<0.05). The Innovative Support Vector Machine algorithm has a mean accuracy of 94.10 and a standard deviation of 2.084. The algorithm is 83.16 and 1.865 for Random Forest.

A comparison of the Random Forest and Innovative Support Vector Machine algorithms is necessary in order to increase the accuracy of health prioritizing [(“Behavioral Intervention Technologies: Evidence Review and Recommendations for Future Research in Mental Health” 2013)](https://paperpile.com/c/taS6yc/gU4R). There are several benefits to Random Forest over Innovative Support Vector Machine, the most important being its ability to process large, high-dimensional datasets effectively [(“Telehealth in Older Adults with Cancer in the United States: The Emerging Use of Wearable Sensors” 2017)](https://paperpile.com/c/taS6yc/0u45). The Random Forest ensemble technique, which combines many decision trees and averages their predictions, often yields better generalization and robustness [(Liu and Salinas 2017)](https://paperpile.com/c/taS6yc/6SW0). This functionality is crucial in the healthcare industry, as datasets may exhibit complex patterns and varying degrees of class distribution.In clinical practice, one should carefully consider the unique qualities of the dataset, the intended interpretability of the model, and any computing constraints before selecting between Random Forest and Innovative Support Vector Machine.There is no opposite findings in this research.

Innovative Support Vector Machines and Random Forest are compared for healthcare prioritization, highlighting the need of selecting the optimal algorithm based on dataset attributes and clinical requirements [(Choy et al. 2018)](https://paperpile.com/c/taS6yc/o7pO). Future research endeavors should focus on exploring hybrid approaches that leverage the benefits of both algorithms to augment diagnosis accuracy and facilitate tailored treatment strategies [(Singh, Rastogi, and Singh 2016)](https://paperpile.com/c/taS6yc/b5Zi).Though Support Vector Machine may provide superior accuracy and efficiency in certain scenarios, its theoretical assurances and support make it a preferable alternative, particularly when model openness is critical for healthcare practitioners to make decisions.

This method, which combines entropy with Random Forest, offers important implications for clinical practice in addition to advancing machine learning applications in healthcare administration [(Forouzanfar et al., 2024)](https://paperpile.com/c/taS6yc/F8vu). Improved patient outcomes in healthcare conditions could result from this methodology's higher accuracy than older techniques like Innovative Support Vector Machine. This could change early diagnosis and intervention procedures.

The primary constraint on the experiment is the narrow range of features in the dataset that may accurately predict the percentage of accuracy for healthcare prioritizing [(Charlton et al.,2024)](https://paperpile.com/c/taS6yc/zPKo). The accuracy will improve further with additional independent and dependent factors.

The future scope for healthcare emergencies in hospitals is likely to involve advancements in technology, changes in healthcare delivery models, and a focus on improving overall efficiency and patient outcomes.

**CONCLUSION**

The proposed framework for healthcare prioritizing analysis has the accuracy of 94.10% for Innovative Support Vector Machine Algorithm compared with the Random Forest Algorithm having the accuracy of 83.16%. The proposed framework proves that the Innovative Support Vector Machine has better significant accuracy than the Random Forest 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.

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**TABLES AND FIGURES**

**Table 1.** The mean values for the Innovative Support Vector Machine is 94.10,While this mean for Random Forest is 83.16. The standard deviations for both algorithms are 2.084 and 1.8625 respectively.

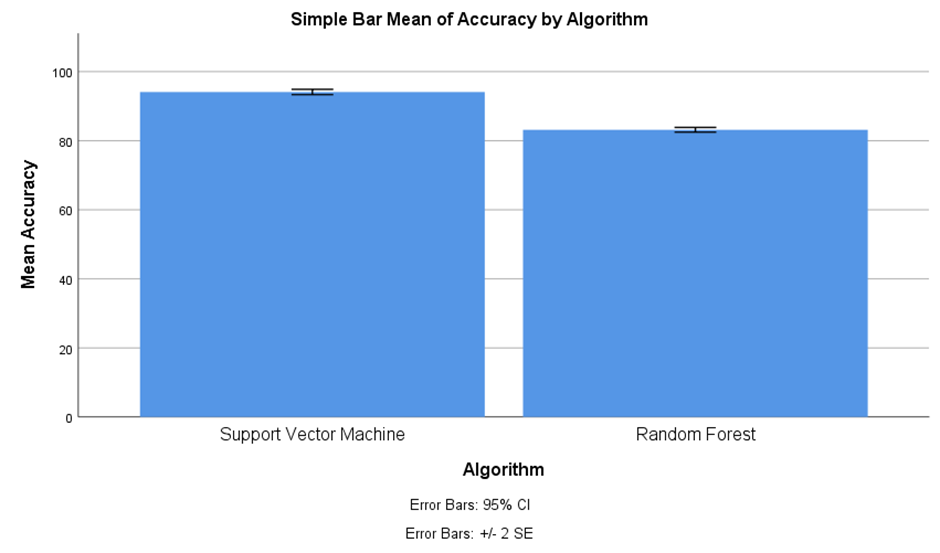
**Group Statistics**

|  | **Algorithm** | **N** | **Mean** | **Std.Deviation** | **Std.Error Mean** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | **Support Vector Machine** | 30 | 94.10 | 2.084 | .380 |
| **Random Forest** | 30 | 83.16 | 1.8625 | .341 |

**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.

**Independent Samples Test**

|  | **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** | .239 | .627 | 21.436 | 58 | .000 | 10.946 | .511 | 9.924 | 11.968 |
| **Equal variances not assumed** |  |  | 21.438 | 57.301 | .000 | 10.946 | .511 | 9.923 | 11.968 |



**Fig. 1.** The Innovative Support Vector Machine Algorithm outperforms the Random Forest Algorithm with 94.10% versus 83.16% accuracy, and slightly superior standard deviation. The comparison is depicted on the graph, with the X-axis representing Innovative Support Vector Machine and Random Forest Algorithms and the Y axis reflecting mean size and accuracy with a range of ±2 standard errors.