

TriML- XAI - Predictive Model For Pre-Hospital Triage With Transparency

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I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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DECLARATION

This is to certify that the work is entirely my own and not of any other person, unless explicitly acknowledged (including citation of published and unpublished sources). The work has not previously been submitted in any form to the Sri Lanka Institute of Information Technology or to any other institution for assessment for any other purpose.

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ABSTRACT

TriML- XAI - Predictive Model For Pre-Hospital Triage With Transparency

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This study develops a Machine Learning model to predict pre-hospital triage levels with enhanced transparency, using clinical data such as vital signs and patients' chief complaints. Accurate triage is essential to prioritize high-risk patients in emergencies. The study evaluates multiple models, including Logistic Regression, Random Forest, Gradient Boosting, and an FCDNN with various embeddings. Voting models were also tested, combining Logistic Regression, Random Forest, and Gradient Boosting. Initial evaluation using a REST API-based test framework showed that each model performed best at specific triage levels. The FCDNN with GloVe embeddings was selected for triage level 1, achieving 90% accuracy, 1.00 recall, and a 0.99 F1-score in identifying high-risk cases. For triage levels 2 and 3, the Random Forest model performed well, with a recall of 0.83, an F1-score of 0.65, and an accuracy of 90%. For triage levels 4 and 5, Logistic Regression was chosen, with a recall of 0.74, an F1-score of 0.81, and an accuracy of 60%. These results led to a novel ensemble approach that enhances the accuracy. The proposed ensemble approach operates through three specialized APIs corresponding to the FCDNN model, Random Forest model, and Logistic Regression model. Upon receiving a user request, the Ensemble API invokes these three APIs to generate individual triage level predictions. These predictions are then combined using a Hard Voting mechanism, where the triage level with the majority vote is selected as the final prediction. If the models produce conflicting results (each predicting a different triage level), the system applies weighted voting, assigning weights to models based on their F1-scores to determine the most appropriate outcome. Transparency is enhanced using SHAP, providing healthcare professionals with insights into feature contributions for each prediction. SHAP values reveal the factors influencing a model's decision, helping doctors and responders understand why a particular triage level was assigned. This added interpretability fosters trust, making the model a reliable tool in critical, time-sensitive medical settings.

SHAP: SHapley Additive exPlanations FCDNN: Fully Connected Deep Neural Network

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