UDC 004

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THE ROLE OF SYMPTOM SEVERITY IN IMPROVING NAIVE BAYES-BASED FIRST AID DIAGNOSIS ACCURACY

The increasing adoption of machine learning in critical domains, such as first aid and emergency medicine, introduces unique challenges, particularly concerning the quality and nature of training data. Medical datasets are often characterized by severe class imbalance, where common, non-life-threatening conditions vastly outnumber rare but critical emergencies. While the Naive Bayes classifier is prized for its simplicity and speed, this data skew can significantly compromise its predictive accuracy, especially for the vital minority classes, as detailed in a critical review of machine learning models in emergency systems [1].

Standard implementations of the algorithm may learn to ignore rare symptoms that could indicate a serious condition, instead defaulting to the most probable, benign diagnosis. This study proposes and evaluates a method to enhance the Naive Bayes classifier's performance by incorporating symptom severity as a key feature, thereby providing a stronger signal for the model to correctly identify critical first aid situations and improve overall diagnostic reliability [2]. A fundamental vulnerability of the Naive Bayes classifier is its reliance on prior probabilities derived directly from the training data. This reliance can lead to an unacceptably high rate of false negatives for critical cases, a common issue with imbalanced data that has been studied extensively.

By introducing a symptom severity score, we move beyond a simple binary representation of "symptom present" or "symptom absent." Instead, a feature like "pain level" could be graded on a scale, or a symptom like "bleeding" could be qualified as "minor" or "severe." This added layer of information provides the model with a more nuanced understanding of the clinical context, allowing it to correctly weight the importance of certain symptom combinations that may point to a rare, but serious, condition. To test this hypothesis, this research will use a simulated first aid dataset representative of real-world class distributions. The dataset will be carefully annotated to include a severity score for each symptom, allowing for a direct comparison of models. We will train two separate Naive Bayes classifiers: a baseline model trained on the raw, imbalanced data, and a second model that includes the engineered severity feature [3]. The performance of both models will be critically assessed using metrics beyond simple accuracy, specifically focusing on the recall and F1-score for the minority class, which are crucial for understanding and mitigating the effects of class imbalance on classifiers.

A detailed analysis of the confusion matrices will also be conducted to pinpoint any reduction in false negatives, which is the primary objective of this research. The outcomes of this study hold significant potential for practical application in emergency response systems. If our findings demonstrate that the symptom severity feature substantially improves the Naive Bayes classifier's ability to detect critical conditions, it will provide a simple yet powerful design pattern for developers [4].

Ultimately, this research aims to contribute to the development of more effective automated diagnostic tools in healthcare, where the accuracy of a diagnosis can directly impact patient safety and survival. While this study focuses on the Naive Bayes classifier, the methodology of incorporating a severity feature can be extended to other machine learning models. Future work could explore the application of this approach to more complex algorithms, such as support vector machines or neural networks, to determine if similar gains in performance can be achieved [5].

In conclusion, the data imbalance inherent in first aid datasets is a major obstacle for the Naive Bayes classifier. However, by strategically incorporating symptom severity as a feature, we can provide the model with the necessary information to overcome its biases and make more accurate predictions, a concept similar to over-sampling techniques designed for imbalanced data.

References:

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