

## Discussion

### Answering the Predictive Question:

The central question guiding our analysis is: “Can we predict the likelihood of a heart attack in a patient using their age, Troponin, and KCM enzyme levels?” To address this, we developed three distinct classifiers. The first model predicts heart attack risk based on two factors: age and Troponin levels. The second model utilizes age and KCM enzyme levels as its predictive variables. Lastly, the third model combines all three predictors: age, Troponin, and KCM enzyme levels, for a more comprehensive analysis. These models aim to provide insights into the potential for using KNN classification models in medical diagnostics, particularly in the rapid and accurate identification of heart attack risks.

### Summary of Findings:

Our analysis revealed significant differences in average Troponin and KCM enzyme levels between patients with positive and negative heart attack diagnoses, while other factors such as blood pressure did not exhibit notable disparities. These findings led us to incorporate Troponin and KCM enzyme levels in our KNN classification models.

### Model Evaluation:

- **Model 1 (Age and Troponin):** Exhibited a strong correlation between Troponin levels and age in distinguishing heart attack occurrences, with an accuracy of approximately 79% and a false negative rate of 8.2%.
- **Model 2 (Age and KCM Enzyme):** Demonstrated a moderate predictive capability, with an accuracy of 67% and a higher false negative rate of 41.8%.
- **Model 3 (Age, Troponin, and KCM Enzyme):** Though it improved accuracy to 82%, the model suffered from an increased false negative rate of 28.48%, indicating a trade-off between accuracy and the risk of missing diagnoses.

Model 1 was selected as the most promising due to its high accuracy and relatively low false negative rate. This decision is justified as it provides a balanced approach, prioritizing both the correct identification of heart attacks and minimizing the risk of overlooking potential cases. In a clinical setting, the consequences of false negatives are particularly critical, and thus, a model with a lower false negative rate is preferred even if it sacrifices some accuracy.

### About False Negative in the Model:

A false negative in this context refers to a case where the model incorrectly predicts a patient as not having a heart attack when they actually do. This is a critical aspect of our evaluation, as a high false negative rate could lead to missed diagnoses in clinical settings.

### Impact and Implications:

The ability to predict heart attacks using these models could significantly enhance diagnostic processes in emergency settings, potentially increasing survival rates. The incorporation of these models as auxiliary diagnostic tools, providing rapid assessments based on age and enzyme levels, could aid in timely decision-making. However, the variation in accuracy and false negative rates between models underscores the need for careful consideration in clinical applications.

#### **Advantages and Limitations of KNN in This Context:**

KNN classification offers simplicity and efficiency but is constrained by the size and quality of the dataset. The high false negative rates in some models suggest a need for model refinement and possibly exploring alternative or complementary machine learning techniques, such as neural networks for deeper analysis.

#### **Future Directions:**

This study opens avenues for several future inquiries:

- Can expanding the dataset or employing more complex models like neural networks enhance predictive accuracy and reduce false negatives for heart attack diagnostics?
- What other physiological or demographic factors could be integrated into the heart attack prediction model to improve its predictive power of KNN classification?
- How do these models perform in diverse patient populations, and what are the implications for personalized medicine?

In conclusion, our project presents a promising step towards leveraging data classification in cardiac emergency scenarios, though it also highlights the critical balance between model accuracy and clinical applicability. Further research is warranted to optimize these models for real-world medical settings.