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Harnessing Hybrid Intelligent Models for Analyzing Musculoskeletal Mortality: A Data-Driven Approach

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Abstract: This paper addresses the critical challenges in characterizing musculoskeletal mortality, a prevalent and serious non-communicable condition affecting nearly one in three women and one in five men over the age of 50 worldwide. Globally, musculoskeletal mortality impacts approximately 200 million women, with prevalence rates of 23.1 in women and 11.7 in men, reaching its highest incidence in Africa at 39.5. This study leverages extensive datasets and advanced computational techniques, including machine learning models such as Decision Trees (DT), Artificial Neural Networks (ANN), and a hybrid DT-ANN approach, to improve diagnosis, treatment options, and disease management. By integrating data-driven methodologies with medical imaging, this innovative approach aims to enhance diagnostic accuracy and optimize patient outcomes. Furthermore, the proposed framework facilitates personalized treatment strategies through comprehensive analyses of clinical and genetic information, reinforcing the role of cutting-edge technology in transforming musculoskeletal mortality research and healthcare practices.

Keywords: Healthcare issues, diagnosis of Musculoskeletal mortality, Artificial Neural Network, Decision Tree, the hybrid DT-ANN, machine learning technique.

1 Introduction

Musculoskeletal mortality is a widespread non-communicable condition affecting millions worldwide, particularly among older adults. Statistics indicate that approximately one in three women and one in five men over the age of 50 are affected, significantly increasing the risk of fractures and severe health complications [1]. Despite medical advancements, diagnosing and treating musculoskeletal mortality remains challenging, primarily due to late detection—often only after fractures occur—and the urgent need for more personalized and effective treatment strategies [2].

Research Problem

A major challenge in musculoskeletal mortality diagnosis is its reliance on conventional methods such as dual-energy X-ray absorptiometry (DXA) to assess bone mineral density (BMD), which may fail to detect the disease in its early stages. Additionally, patients respond differently to existing treatments, highlighting the need for a more precise approach to risk prediction and personalized therapy. Recent advancements in artificial intelligence and machine learning have facilitated the analysis of vast medical datasets, uncovering novel patterns that enhance diagnosis, assess risk more accurately, and optimize treatment strategies

The Study Objective

Enhance musculoskeletal mortality diagnosis by leveraging advanced machine learning models, including Decision Trees (DT) and Artificial Neural Networks (ANN), to enable early disease detection. Develop personalized treatment strategies by analyzing patient responses to various therapies using artificial intelligence algorithms, ensuring tailored treatment plans for each individual. Improve disease management through predictive analytics to monitor disease progression over time, integrating wearable devices and digital health data

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to assess fracture risks and implement effective preventive measures

Significance of the Study

This research plays a crucial role in providing technologically advanced solutions to modern challenges in musculoskeletal mortality diagnosis and treatment. By leveraging artificial intelligence and machine learning, it enhances diagnostic accuracy, reduces healthcare costs, and improves patient outcomes. Moreover, the findings may contribute to the development of clinical decision support systems, empowering physicians to make more precise and effective treatment decisions

Research Framework

This research is structured into multiple sections, beginning with a theoretical framework that outlines the scientific foundations of musculoskeletal mortality and the key challenges in its diagnosis and treatment. Section 2 explores contemporary AI and machine learning methodologies applied in the medical field, with a focus on their role in diagnosing and treating musculoskeletal mortality. Section 3 presents the results and evaluates the effectiveness of various models, comparing the performance of traditional and hybrid approaches. Finally, Section 4 provides conclusions and future recommendations, summarizing the key findings and identifying potential directions for further research. This study aims to introduce innovative solutions that enhance healthcare quality and support clinicians in making informed decisions through precise medical data analysis.

2 Models Employed in the Study

2.1 Decision Tree (DT)

A decision tree is a machine learning model that employs a tree-like structure to make predictions or classifications based on a set of attributes[3]. This model operates by recursively partitioning data into branches according to specific criteria until a final outcome is reached [4]. Due to its intuitive structure, the decision tree is widely used in various domains, including medical diagnosis, where it facilitates transparent decision-making.

The decision tree algorithm divides data into progressively smaller subsets, with each partition determined by the attribute that offers the most effective class separation [5]. Within this hierarchical structure, each node represents a test on a specific attribute, branches correspond to the possible outcomes of that test, and leaf nodes indicate the final classification or predicted values [6]. However, deep decision trees can lead to overfitting, where the model captures noise rather than meaningful patterns in the data. To address this issue, techniques such as pruning—removing less significant branches—are employed to improve generalization and robustness [7]. One of the key advantages of decision trees is their interpretability, as they provide a clear and understandable decision-making process, making them more accessible than many other machine learning models [8]. Decision trees play a crucial role in diagnosing musculoskeletal mortality by categorizing patients based on various health determinants, including age, gender, family history, and bone mineral density [9, 10]. By systematically analyzing these factors, decision trees can assist in early detection and risk assessment. Moreover, they can be combined with other methodologies, such as artificial neural networks (ANN), to enhance diagnostic precision and reduce errors, thereby improving patient outcomes [11]. This hybrid approach leverages the interpretability of decision trees alongside the predictive power of ANN, resulting in a more robust diagnostic framework.

2.2 Artificial Neural Networks (ANN)

An Artificial Neural Network (ANN) is a computational framework inspired by the architecture and functioning of the human brain. It is widely used in machine learning for tasks such as classification, regression, pattern recognition, and decision-making applications [12]. In the context of musculoskeletal mortality, ANN is instrumental in identifying risk factors by analyzing patterns in bone mineral density (BMD), clinical risk indicators, and medical imaging data, such as X-rays or dual-energy X-ray absorptiometry (DXA) scans[13]. Through its ability to detect early warning signs, ANN facilitates the identification of patients at high risk for fractures [14]. Furthermore, ANN-based models assist in creating personalized treatment strategies by predicting the effectiveness of various therapeutic approaches, optimizing medication dosages, and monitoring disease progression over time [15]. ANNs are structured in layers of interconnected nodes, or neurons, each playing a distinct role in data processing. The input layer is responsible for receiving raw data—such as images, numerical values, or text—and each neuron in this layer represents a specific feature of the input data [16]. The hidden layers, which may consist of one or more layers, perform complex calculations using weights, biases, and activation functions. These layers detect patterns and relationships within the data[17]. The final layer, known as the output layer, generates the predicted result, such as a classification label or numerical value [18]. The learning process within an ANN involves several steps. First, during forward propagation, the input data passes through the layers, and an initial output is generated. Then, the loss function, such as Mean Squared Error or Cross-Entropy, is used to calculate the error (or loss) between the predicted output and the true values[19]. To refine the model, backpropagation is employed, where the error is propagated back through the network to adjust the weights using optimization techniques like Gradient Descent or more advanced methods like Adaptive Moment Estimation (Adam) and Root Mean Square

Propagation (RMSprop). Finally, the weights are updated to minimize the error, improving the accuracy and efficiency of the network.

3 Hybrid DT- ANN

The integration of a Decision Tree (DT) with a Multilayer Perceptron (MLP) neural network creates a hybrid model that combines the strengths of both approaches, offering improved classification accuracy and enhanced interpretability [20,21]. There are several ways to combine these two models, each of which leverages the unique capabilities of decision trees and neural networks to optimize performance.

One method involves using the decision tree as a preprocessing step for the MLP. In this approach, the decision tree is first employed to partition the dataset into smaller, more homogeneous subsets [22]. A separate multilayer perceptron neural network is then trained on each of these subsets corresponding to the leaf nodes of the decision tree [23]. This method not only enhances interpretability but also takes advantage of the MLP's ability to capture complex, non-linear relationships within the data [24].

Another variation of the hybrid approach uses the decision tree to direct data to an MLP classifier at the leaf nodes, rather than directly assigning class labels. This enables the MLP to refine the classification decision made by the decision tree, improving overall accuracy [26]. In this case, the MLP at each terminal node acts as a secondary classifier, enhancing the decision-making process by learning intricate patterns in the data that might be missed by the tree alone. Alternatively, the MLP can support the decision tree by identifying optimal splits, replacing traditional splitting criteria such as Gini impurity or entropy [25]. This integration leads to a more efficient and resilient decision tree model, which can adapt better to complex datasets.

The benefits of the hybrid DT-MLP model are numerous. By combining rule-based decision trees with the non-linear processing capabilities of the MLP, this approach increases accuracy and improves generalization compared to standalone decision trees. Additionally, the decision tree structure remains interpretable, making the model more transparent and easier to understand. Furthermore, this hybrid approach effectively handles complex relationships in the data, overcoming the limitations of individual decision trees, which may fail to capture certain patterns [26].

Figure 1 illustrates the hybrid Decision Tree-MLP model, showcasing how the integration of decision trees with Multilayer Perceptron (MLP) networks enhances diagnostic accuracy. The figure provides a visual representation of how decision trees partition data into homogeneous subsets, with each subset being further processed by the MLP for improved classification outcomes. This combination of rule-based and non-linear modeling techniques leads to a more robust and accurate system for diagnostic purposes.

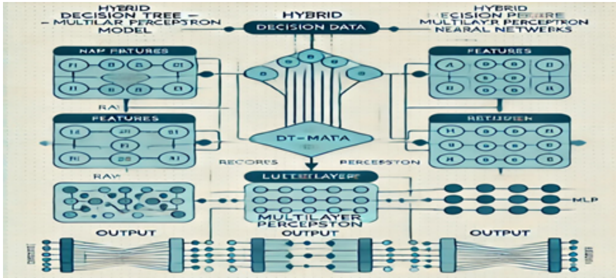

Fig. 1: Hybrid ARIMA-ANN Diagram

4 Evaluating the performance of the models

In this section, data from the Australian National Mortality Database, which recorded 12,474 deaths attributed to musculoskeletal-related causes between 2011 and 2021, are utilized to build and evaluate predictive models. This dataset serves as a foundation for comparing various machine learning approaches, allowing us to assess their effectiveness in predicting musculoskeletal-related mortality. The following section offers a comparative analysis of these models, emphasizing their predictive performance, strengths, and limitations, and provides insights into their applicability for forecasting musculoskeletal-related deaths.

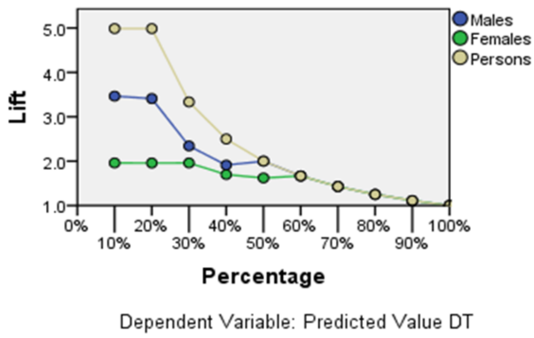

Fig. 2: Left Char for hybrid DT-ANN

The Hybrid DT-ANN lift chart demonstrates higher lift values and a more gradual decline, indicating superior predictive capability and generalization compared to the ANN model. This suggests that the Hybrid DT-ANN

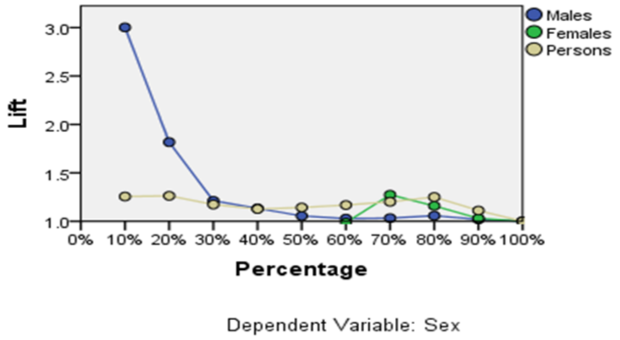

Fig. 3: Left Chat for ANN

model outperforms the ANN, as evidenced by its consistently higher lift values, reflecting its ability to better identify and rank the most relevant cases for prediction.

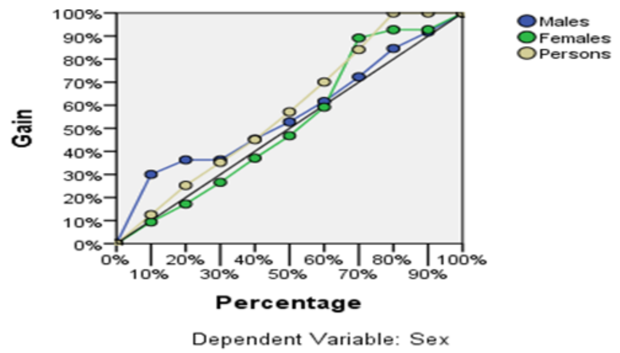

Fig. 4: Gain Chart for ANN

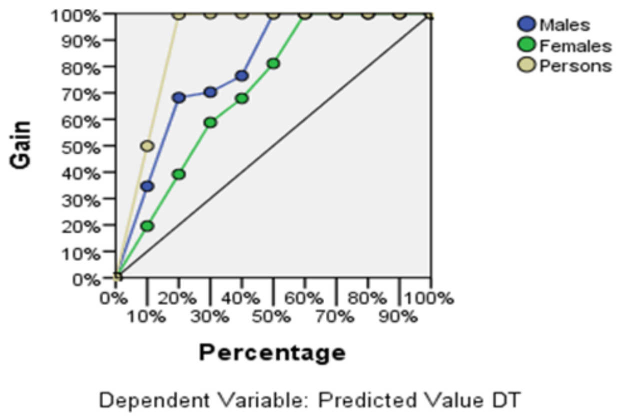

Fig. 5: Gain Chart for DT-ANN

Table 1: Table1 Models Performance

Model	Performance (AUC, Accuracy)	Reliability
ANN Model	AUC:555	Weak
Decision Tree Model	High risk (62.2% error rate)	Poor
Hybrid DT-ANN	AUC: 0.927	Excellent

In Figure 4, the AUC values for all predicted classes are below 0.56, indicating relatively poor performance. In contrast, Figure 5 shows that the AUC values exceed 0.9 across all predicted classes, showcasing a significant improvement. This stark difference in performance highlights that the hybrid Decision Tree-Artificial Neural Network (DT-ANN) model substantially outperforms the ANN model, underscoring its superior predictive capability and effectiveness in classification tasks. The higher AUC values achieved by the hybrid model reflect its enhanced ability to discriminate between classes and provide more accurate predictions.

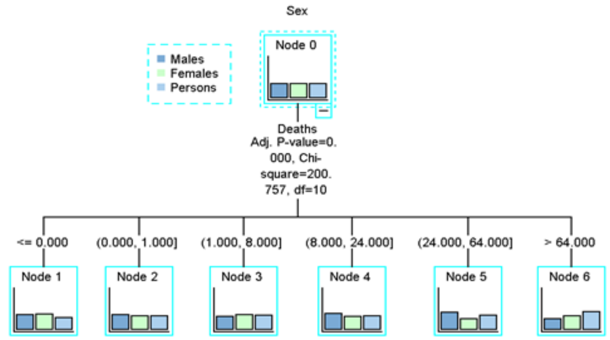

Fig. 6: Decision Tree Diagram

The diagram in figure 6 illustrates a 6-node decision tree utilizing the CHAID approach. Despite its simplicity, the model's weakness is evident, as it is associated with a 62.2% error rate, reflecting its limited predictive performance. To provide a clearer comparison of the model's effectiveness, the following table presents a comparison of the three models—ANN, Decision Tree, and Hybrid DT-ANN—based on key performance metrics such as Area Under the Curve (AUC) and accuracy. This table highlights the strengths and limitations of each model, providing insights into their relative effectiveness in predicting musculoskeletal-related deaths.

The ANN model's AUC of 0.555 indicates poor performance in classification, suggesting that it struggles to effectively differentiate between the predicted classes. The Decision Tree (CHAID) model fares even worse, with a high error rate of 62.2%, making its predictions unreliable. In contrast, the Hybrid DT-ANN model demonstrates superior performance, with an AUC of 0.927, highlighting its effectiveness in classification tasks. This substantial improvement in AUC underscores the Hybrid DT-ANN model's ability to provide more accurate and reliable predictions compared to both the ANN and Decision Tree models.

5 Conclusion

This study evaluates the performance of three distinct predictive models—Artificial Neural Networks (ANNs), Decision Trees (DT), and a Hybrid DT-ANN model that combines the strengths of decision trees and artificial neural networks—for forecasting musculoskeletal mortality rates. The findings reveal that the hybrid model outperforms both the ANN and DT models, offering superior prediction accuracy and robustness. The results from the Gain Chart, Lift Chart, and Area Under the Curve (AUC) all support this conclusion, further confirming the enhanced efficacy of the hybrid model.

While all three models provide valuable insights into predicting musculoskeletal mortality trends, the Hybrid DT-ANN model stands out for its superior accuracy and reliability. The improved performance of hybrid models can be attributed to their ability to leverage the strengths of multiple algorithms, which enhances generalization and reduces classification errors. By combining rule-based decision trees with deep learning neural networks, hybrid models excel in handling complex, nonlinear relationships within diverse datasets.

Furthermore, the adaptive learning capabilities of hybrid models contribute to their robustness, allowing them to continuously learn from evolving data patterns. This adaptability makes them particularly effective for predicting long-term trends, especially in dynamic environments like healthcare. Hybrid models offer an optimal solution for predictive analytical, particularly in healthcare applications, due to their ability to manage complex and variable changes in data.

This research underscores the critical role of predictive modeling in analyzing large-scale healthcare data, such as musculoskeletal mortality rates, and monitoring recovery patterns following musculoskeletal disorders. The findings highlight the importance of employing advanced machine learning techniques to enhance the precision of healthcare forecasting and strategic planning. These insights are particularly valuable for policymakers and healthcare professionals, providing a data-driven foundation for informed decision-making and efficient resource allocation in public health management.

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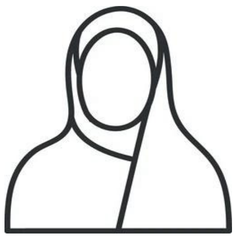

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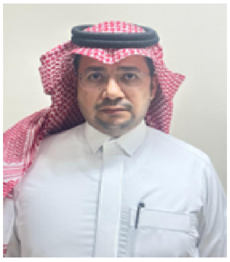

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