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APPLICATION OF ARTIFICIAL INTELLIGENCE FOR HEALTH STATUS CLASSIFICATION IN MILITARY PERSONNEL

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ABSTRACT
The health monitoring of military personnel is critical for sustaining operational readiness and minimizing medical risks. In this study, we present an artificial intelligence-driven application that classifies the health status of service members based on two simple medical parameters: heart rate and body weight. The system integrates two complementary approaches: supervised learning using decision trees and unsupervised learning with the K-Means algorithm. Experimental evaluation demonstrates that the decision tree achieved an accuracy of 90%, as confirmed by the confusion matrix, while the K-Means method identified distinct clusters aligned with clinically relevant health profiles: healthy, cardiac risk, and metabolic risk. These results highlight the potential of artificial intelligence to be effectively integrated into military medical monitoring systems, supporting early diagnosis and enhancing the efficiency of health assessment processes.

KEYWORDS: artificial intelligence, decision tree, clustering, military health, medical data

1. Introduction

The health status of military personnel is a critical factor in maintaining combat readiness and operational effectiveness. Service members are often exposed to extreme physical and psychological stress, and the early identification of medical risks contributes to accident prevention, increased resilience, and the optimization of medical interventions.

In recent years, artificial intelligence (AI) has become an increasingly valuable tool in the medical domain, offering advanced methods for analysis, classification, and diagnosis (Bishop, 2006; Han, Kamber & Pei, 2011). Rajpurkar et al. (2022) highlighted the growing impact of AI systems in clinical diagnosis and decision support, emphasizing their potential to complement medical expertise. In particular, supervised classification algorithms such as decision trees (Quinlan,

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1993), and unsupervised approaches such as K-Means (Lloyd, 1982), have proven effective in processing medical data. Relevant studies show that AI can achieve performance levels comparable to those of human specialists in detecting certain conditions (Esteva et al., 2017; Rajkomar, Dean & Kohane, 2019; Topol, 2019).

This paper describes an application that employs artificial intelligence algorithms to classify the health status of military personnel, based on simple parameters such as heart rate and body weight. The system implements two complementary approaches:

- supervised learning, through decision trees, to predict a diagnosis based on training data;
- unsupervised learning, through K-Means, to identify groups with similar health profiles without using predefined labels.

It should be noted that the dataset used in this study is limited in size and diversity, and was designed with a demonstrative purpose, namely to highlight the functionality and applicability of artificial intelligence in early diagnosis. Expanding the dataset with a larger number of medical parameters would significantly increase the accuracy and robustness of the models.

The aim of this study is to demonstrate the applicability of artificial intelligence in monitoring the health of military personnel, emphasizing the advantages of using simple, interpretable, and efficient algorithms that can be integrated into medical decision-support systems. Recent studies have also emphasized the growing role of artificial intelligence in military medicine, highlighting its potential to enhance diagnostic accuracy, medical logistics, and decision-making under operational constraints (Bahramnezhad et al., 2025). Given the demonstrative nature of the study and the relatively small dataset, this paper illustrates the principle of operation and the potential for extending the methodology to much larger and more diverse clinical datasets.

2. Materials and Methods

2.1. Technologies and Application Architecture

The application was developed using the Django framework (Python), which follows the MVT (Model-View-Template) architectural pattern:

- **Model (M)** – defines the data structure (medical parameters such as heart rate, weight, and diagnosis).
- **View (V)** – contains the application logic: retrieving the data, applying classification/clustering algorithms, and transmitting the results to the interface.
- **Template (T)** – the presentation layer, where results and graphs are displayed in the browser in a user-friendly format.

In addition to Django, the application integrates several Python libraries:

- Data processing:
  - *Pandas* – for handling Excel files and datasets,
  - *NumPy* – for fast numerical operations.
- Artificial intelligence algorithms:
  - *Scikit-learn* – implementing supervised classification algorithms (Decision Tree) and unsupervised clustering (K-Means), as well as evaluation measures (accuracy, confusion matrix, Silhouette score).
- Data visualization:
  - *Matplotlib* – for generating classification and clustering plots,
  - *Seaborn* – for advanced statistical visualizations and improved presentation.

This combination of technologies enables the development of a complete application that processes raw medical data, applies machine learning algorithms, and displays the results through a user-friendly web interface.

2.2. Datasets Used

For this demonstrative study, two Excel files were used:

- **training_data.xlsx** – the training set (50 records),
- **test_data.xlsx** – the test/validation set (10 records).

The column structure is identical:

- **Name** – generic identifier (Soldier 1, Soldier 2, …),
- **Heart rate** – beats per minute (bpm),
- **Weight** – body weight (kg),
- **Diagnosis** – medical label (Normal, Hypertension, Diabetes, Heart disease, Obesity).

The dataset is small in size and was designed solely for demonstrative purposes. In a real-world application, the use of an extended, diverse, and multidimensional dataset (including blood pressure, blood glucose, and medical history) would considerably improve the performance of the algorithms.

The training set contains 50 fictitious records regarding the soldiers' heart rate, weight, and diagnosis, used to train the classification algorithm. The structure and a sample of values from this set are presented in Table no. 1.

Table no. 1

Training set (training_data.xlsx – 50 records)

Name	*Heart rate (bpm)*	*Weight (kg)*	*Diagnosis*
Soldier 14	82	91	Hypertension
Soldier 40	86	72	Diabetes
Soldier 31	82	93	Diabetes
Soldier 46	82	119	Obesity
…	…	…	…
Soldier 29	100	86	Heart disease
Soldier 39	86	92	Diabetes
Soldier 25	82	91	Hypertension

To evaluate the model, a separate set of 10 records was used, distinct from the training data. This set has the same structure and allows for the verification of the model's performance on unseen data. Its content is shown in Table no. 2.

Table no. 2

Test set (test_data.xlsx – 10 records)

Name	*Heart rate (bpm)*	*Weight (kg)*	*Diagnosis*
Soldier 1	72	70	Normal
Soldier 2	95	85	Hypertension
Soldier 3	110	90	Heart disease
Soldier 4	65	68	Normal
Soldier 5	85	95	Diabetes
Soldier 6	102	100	Hypertension
Soldier 7	78	80	Normal
Soldier 8	120	110	Heart disease
Soldier 9	88	105	Obesity
Soldier 10	99	92	Hypertension

In machine learning, datasets are usually divided into three subsets (training, validation, and test). In this demonstrative study, given the limited amount of data and the absence of hyperparameter optimization, we used only two subsets: training and test.

2.3. Algorithms Used

For the data analysis, two fundamental algorithms from the field of Artificial Intelligence were applied.

2.3.1. Decision Trees (supervised classification)

- Trained on labeled data (heart rate, weight → diagnosis).
- Uses the Gini index to select the most relevant attributes (Quinlan, 1993; Bishop, 2006).
- Formula for the Gini impurity:

$$Gini(t) = 1 - \sum_{i=1}^{C} p_i^2 \quad (1)$$

where:

– $\boldsymbol{p_i}$ – represents the proportion of instances from class ***i*** in node ***t***, and

– $\boldsymbol{C}$ is the total number of possible classes (categories into which the data can be classified).

The model returns a predicted diagnosis for each soldier.

The classifier's performance was evaluated using accuracy (number of correct predictions/ total instances) and the confusion matrix (Fawcett, 2006). Accuracy is defined as the ratio of correctly classified instances to the total number of instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

where:

- TP = True Positive,
- TN = True Negative,
- FP = False Positive,
- FN = False Negative.

The confusion matrix provides a detailed view of correct predictions and errors for each diagnostic class (Figure no. 2).

2.3.2. K-Means algorithm (unsupervised clustering)

This algorithm partitions the data into k groups by maximizing the similarity within clusters (Lloyd, 1982; Han, Kamber, & Pei, 2011).

To validate the quality of the clusters, the Silhouette score was used (Rousseeuw, 1987):

$$S(i) = \frac{b(i)-a(i)}{max\,\{a(i),b(i)\}} \quad (3)$$

where ***a(i)*** is the average distance between element ***i*** and all other members of its own cluster, and ***b(i)*** is the minimum average distance between element ***i*** and members of another cluster.

Values close to 1 indicate a good separation between clusters.

To obtain the global score (in this case, 33.34%), the average of all individual values is computed:

$$S = \frac{1}{n} \sum_{i=1}^{n} S(i) \quad (4)$$

where ***n*** is the total number of elements and ***i*** is the index of each data point in the analyzed set. The values of ***S*** fall within the interval [−1,1], where values close to 1 indicate well-separated clusters, values near 0 suggest overlapping clusters, and negative values indicate that some elements may have been assigned to incorrect clusters.

2.3.3. Rationale and Limitations of Feature Selection

This study intentionally used only two basic physiological parameters – heart rate and body weight – as input variables. The aim was not to build a complete diagnostic system, but to demonstrate the functional potential of AI algorithms in early-stage health monitoring scenarios. Additional medical parameters such as blood pressure, blood glucose, height, age, or gender would significantly increase the accuracy and robustness of the models. This limitation is inherent to the demonstrative nature of the study and is acknowledged accordingly.

3. Results

3.1. Decision Tree

The Decision Tree algorithm was trained on the dataset *training_data.xlsx* and tested on *test_data.xlsx*. The decision tree achieved an accuracy of 90%. The model's predictions are shown in Table no. 3, while Figure no. 1 illustrates the decision tree built on the basis of heart rate and weight. Figure no. 2 presents the confusion matrix for the test set, where the predominance of correct values along the main diagonal can be observed.

Table no. 3
The model's predictions

Name	*Actual diagnosis*	*Heart rate (bpm)*	*Weight (kg)*	*Predicted diagnosis*
Soldier 1	Normal	72	70	Normal
Soldier 2	Hypertension	95	85	Heart disease
Soldier 3	Heart disease	110	90	Heart disease
Soldier 4	Normal	65	68	Normal
Soldier 5	Diabetes	85	95	Obesity
Soldier 6	Hypertension	102	100	Heart disease
Soldier 7	Normal	78	80	Diabetes
Soldier 8	Heart disease	120	110	Heart disease
Soldier 9	Obesity	88	105	Obesity
Soldier 10	Hypertension	99	92	Diabetes

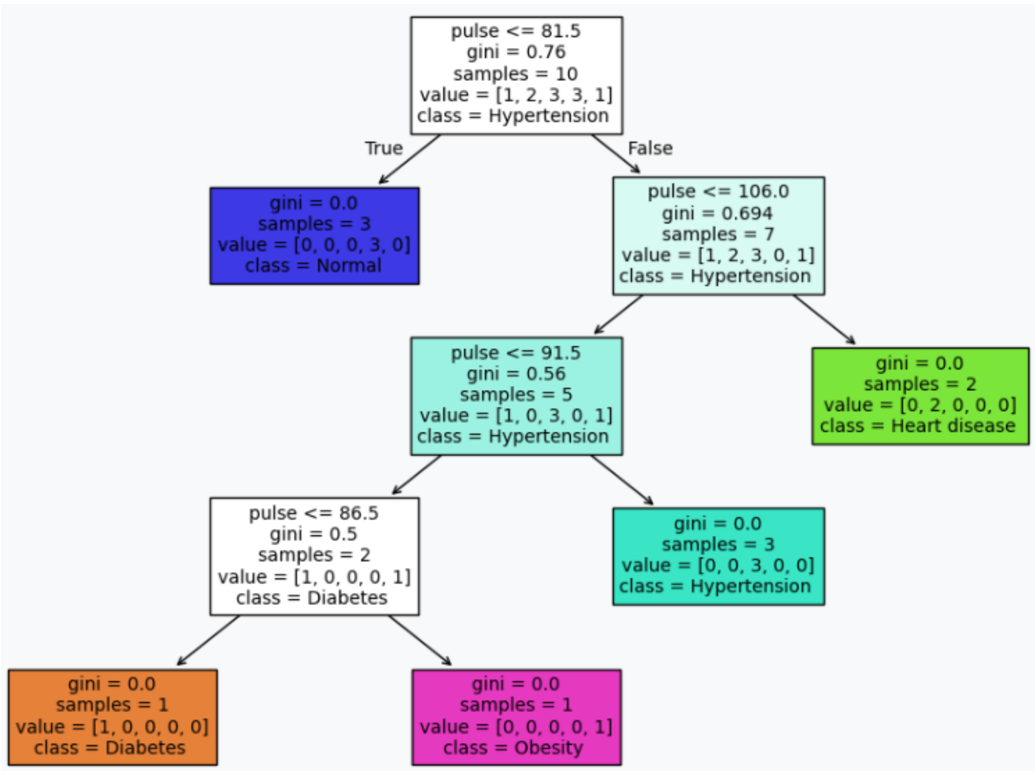

Figure no. 1: *Structure of the decision tree based on heart rate and weight*

Interpretation of the tree:

- The first split rule is determined by heart rate ≤ 81.5 bpm.
- The terminal nodes reflect the main diagnostic classes: Normal, Hypertension, Diabetes, Obesity, Heart disease.

The branches demonstrate how combinations of heart rate and weight lead to the final classification.

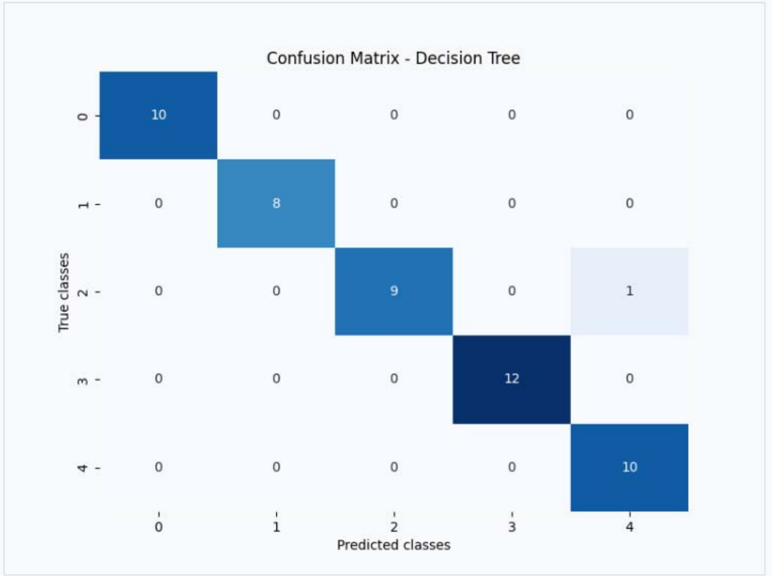

Figure no. 2: *Confusion matrix for the test set*

The confusion matrix (Figure no. 2) provides a detailed representation of the model's classification performance. The diagonal elements correspond to correct predictions, while off-diagonal elements indicate misclassifications. The accuracy value of 90% was computed as the ratio between correctly predicted cases and the total number of test cases, confirming that the model can successfully distinguish the majority of diagnostic classes.

3.2. Unsupervised Clustering (K-Means)

The K-Means algorithm (Lloyd, 1982; Han, Kamber & Pei, 2011) was applied to the test set *test_data.xlsx* to identify natural groupings based on heart rate and weight. A number of k=3 clusters was obtained, with a Silhouette score of 0.3334 (33.34%) (Rousseeuw, 1987). The cluster distribution is shown in Table no. 4.

Table no. 4

Clustering results (test_data.xlsx)

Name	*Heart rate (bpm)*	*Weight (kg)*	*Cluster*	*Cluster description*
Soldier 1	72	70	0	Healthy profile (normal heart rate and weight)
Soldier 2	95	85	1	Cardiac risk (elevated heart rate)
Soldier 3	110	90	1	Cardiac risk (elevated heart rate)
Soldier 4	65	68	0	Healthy profile (normal heart rate and weight)
Soldier 5	85	95	2	Metabolic risk (high weight / obesity / diabetes)
Soldier 6	102	100	1	Cardiac risk (elevated heart rate)
Soldier 7	78	80	0	Healthy profile (normal heart rate and weight)
Soldier 8	120	110	1	Cardiac risk (elevated heart rate)
Soldier 9	88	105	2	Metabolic risk (high weight / obesity / diabetes)
Soldier 10	99	92	1	Cardiac risk (elevated heart rate)

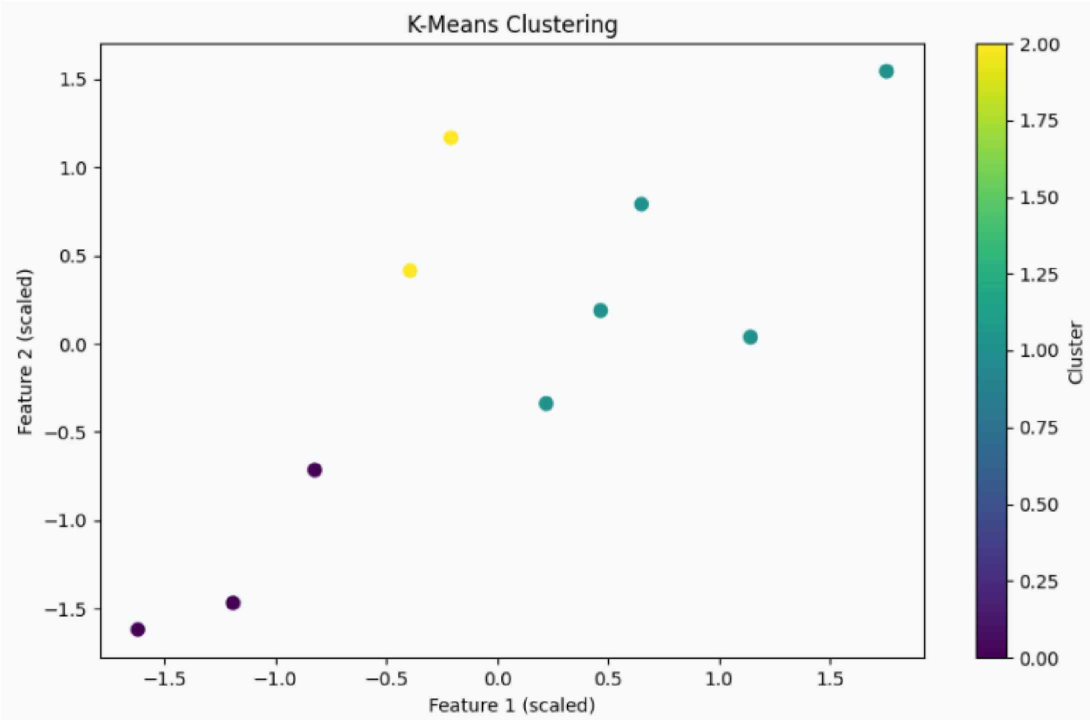

Figure no. 3: *Clustering obtained through K-Means: healthy profile, cardiac risk, and metabolic risk*

Interpretation:

- Cluster 0: healthy profile (balanced values of heart rate and weight).
- Cluster 1: cardiac risk (significantly elevated heart rate).
- Cluster 2: metabolic risk (high weight combined with medium heart rate).

3.3. General Observations

The supervised classifier (Decision Tree) achieved a high accuracy (90%), confirming that simple parameters such as heart rate and body weight can be relevant for an initial health status classification. However, the confusion matrix analysis highlights difficulties in clearly separating closely related diagnoses (e.g., Hypertension ↔ Heart disease or Diabetes ↔ Obesity).

The K-Means clustering, although it yielded a modest Silhouette score (33.34%), enabled the identification of clinically interpretable groups: healthy profile, cardiac risk, and metabolic risk.

These results indicate the potential of the application, while also showing that higher precision would require additional medical variables (e.g., blood pressure, blood glucose, medical history) as well as larger and more diverse datasets.

4. Discussions

The results obtained highlight the potential of artificial intelligence in supporting early medical diagnosis for military personnel. The decision tree demonstrated the ability to generate interpretable rules, making it a valuable tool in clinical contexts where decision transparency is essential. However, the analysis of the confusion matrix revealed misclassifications between closely related diagnoses, such as hypertension and Heart disease or diabetes and obesity. These errors are medically explainable, since these conditions share common risk factors and overlapping symptoms.

An essential aspect is the limited dataset used in the experiment, which served only a demonstrative purpose. In real-world applications, a larger, more diverse, and multidimensional dataset (including variables such as blood pressure, blood glucose, family history, and physical activity level) would allow for clearer diagnostic differentiation and improved algorithm performance.

The unsupervised method (K-Means) succeeded in identifying clinically interpretable groups: healthy profile, cardiac risk, and metabolic risk. Although the Silhouette score obtained was modest, the existence of these clusters indicates that AI can reveal relevant patterns even in limited datasets. In practice, such an approach could be employed for the rapid triage of military personnel by risk level, with detailed assessments subsequently performed by medical professionals.

The integration of AI into military health monitoring systems could contribute to early diagnosis, the prevention of complications, and the optimization of medical resources. Nevertheless, a further stage of validation on larger and more heterogeneous clinical datasets is required to confirm the robustness and applicability of the models.

It is important to emphasize that this study does not aim to provide clinical diagnostic accuracy, but rather to illustrate how AI methods can be conceptually applied to health monitoring in military contexts. The limited dataset and reduced number of features were chosen intentionally to highlight the feasibility and interpretability of the algorithms. Expanding the data volume and including a broader range of health indicators will be part of future development.

5. Conclusions

This study demonstrated that artificial intelligence can be applied to classify the health status of military personnel, even when relying on simple medical parameters such as heart rate and body weight.

The supervised method (Decision Tree) achieved an accuracy of 90%, showing the potential of classification algorithms in identifying conditions such as hypertension, diabetes, obesity, or Heart disease.

The unsupervised method (K-Means) successfully grouped the personnel into clinically meaningful clusters – healthy profile, cardiac risk, and metabolic risk – confirming the usefulness of clustering in detecting hidden patterns.

The results also highlighted the current limitations: a small dataset, minimal medical parameters, and the absence of clinical validation. Nevertheless, the applied methodology remains valid and extensible.

Expanding the dataset with additional medical variables (blood pressure, blood glucose, cholesterol, lifestyle factors) and validating the models on real military health data could transform the application into a practical decision-support tool for early diagnosis and preventive monitoring.

This work demonstrates not only the applicability of AI in military health diagnostics but also its potential to evolve into integrated clinical systems, with direct impact on the health and performance of military personnel.

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