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Predictive Health Architecture 5.0: Evaluation of Cloud-Based Machine Learning Models for Hypertension Detection

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ABSTRACT
This study develops and validates a cloud-based Health 5.0 architecture for the early prediction of arterial hypertension (AHT) through artificial intelligence. A biomedical dataset (N=4,063) from ENSANUT and Kaggle was processed using Microsoft Azure. Three supervised learning models like Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN were evaluated. Training incorporated hyperparameter sweeping and Explainable AI (XAI) techniques to ensure clinical transparency. The ANN model achieved a 91.4% accuracy and an Area Under the Curve (AUC-ROC) of 0.89, significantly outperforming traditional statistical risk scores. Furthermore, the cloud infrastructure demonstrated a response latency of 1.4 seconds, confirming its suitability for real-time applications. The integration of deep learning models within elastic cloud environments facilitates a proactive, scalable, and transparent approach to AHT detection. This architecture provides an efficient decision-support tool for preventive medicine, aligning with the ethical and technical requirements of modern digital healthcare systems.
Keywords - Arterial Hypertension, Artificial Intelligence, Deep Learning, Health 5.0, Microsoft Azure.

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I. INTRODUCTION

In recent decades, chronic degenerative diseases, particularly hypertension, have become major global public health challenges. According to the World Health Organization (WHO), these conditions are the leading cause of death in both developed and developing nations. In Mexico, hypertension is responsible for 18.1% of all deaths, with a 29.9% increase in the mortality rate in recent years [1].

The literature reports that a variation of just 5 mmHg in systolic blood pressure can alter the global prevalence of the disease by 84 million people [2]. Given that external factors affect the outcome in 20% to 45% of consultations [3], AI emerges as a tool to mitigate the margin of error by analyzing hidden patterns in large volumes of historical data.

Despite the severity of this condition, conventional clinical management faces critical limitations. Current diagnosis relies on manual measurements that have up to a 60% error rate due to human factors (García Donaire, SEHLELHA), and on linear risk scales such as the Framingham Risk Score, which fail to capture the nonlinear interactions of complex biomedical variables [4].

In this context, the Health 5.0 paradigm emerges, proposing the transformation of the medical system through the use of Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing to offer personalized and proactive care [5]. Recent research suggests that supervised learning algorithms, such as Support Vector Machines (SVM) and Random Forest, can achieve discrimination capabilities (AUC-ROC) greater than 0.90, far exceeding the average of 0.76 for traditional methods.

The evolution towards Health 5.0 responds to the need for elastic infrastructures that improve the integration and visualization of bioinformatics data [6]. The cloud not only acts as storage, but also as the necessary computational support for efficient and highly accurate preventive systems.

This article presents the design and validation of a Microsoft Azure-based architecture that integrates machine learning models for hypertension prediction. The research aims to bridge the gap between the availability of massive biomedical datasets (ENSANUT/Kaggle) and their intelligent processing, proposing a scalable solution that optimizes decision-making in preventive medicine.

II. METHODOLOGY

The experimental design was structured in four consecutive phases: from the curation of biomedical data to the deployment of predictive models in an elastic cloud environment.

2.1 Data acquisition and preparation

The "Hypertension Mexico" dataset was used, which integrates records from the National Health and Nutrition Survey (ENSANUT) and Kaggle clinical repositories. The original dataset (N = 4,363) has 35 predictive attributes categorized into demographic variables, blood biomarkers (glucose, cholesterol, insulin), anthropometric measurements, and vital signs.

The preprocessing phase, automated in Python, included:

- Cleaning and Filtering: Duplicates were removed using the identifier FOLIO_I and exclusion criteria were applied for records with clinical inconsistencies, resulting in a final sample of 4,063 records.
- Coding: Label Encoding was applied to the sex variable (0: female, 1: male), while the rest of the variables (34 continuous) were kept in numeric format to preserve scalar precision.
- Class Balance: The sample shows a distribution of 64.5% for high-risk cases and 35.5% for low-risk cases.

2.2 Cloud computing architecture

An infrastructure was designed under the Health 5.0 paradigm using Microsoft Azure Machine Learning. The architecture is based on three critical components:

- MLOps Orchestration: Use of Azure ML Workspace for asset management and model version control.
- Elastic Compute: Implementation of auto-scaling virtual machine clusters to guarantee response times of less than 30 seconds.
- Persistence and Availability: Centralized storage in Azure Blob Storage with high-speed protocols for data ingestion during training.

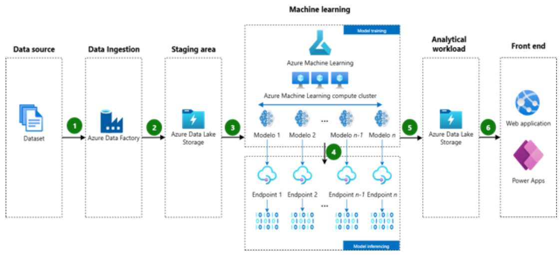

Figure 1. Proposed Model

2.3 Implementation and training of models

Three supervised learning algorithms were evaluated to validate predictive capability

- Support Vector Machine (SVM): Configured with a Radial Basis Function (RBF) kernel to address the nonlinearity of biomarkers.
- Random Forest (RF): Implementation of an ensemble of 100 decision trees with Gini impurity criteria to optimize node splitting.
- Artificial Neural Networks (ANN): Multilayer Perceptron (MLP) architecture with hidden layers (ReLU activation) and a sigmoid output layer for probability estimation.

III. RESULTS AND DISCUSSION

This section presents the findings derived from the execution of predictive models in the cloud environment, analyzing their statistical performance and the technical efficiency of the proposed architecture.

3.1 Comparison of Logarithmic Performance

After hyperparameter scanning in Azure Machine Learning, the three selected models were evaluated using the test dataset (20% of the sample, N = 813). The results demonstrate that algorithms

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based on neural networks and ensembles significantly outperform traditional methods.

Model	Accuracy	AUC-ROC	Recall
SVM	86.5%	0.81	0.84
RF	88.2%	0.83	0.85
ANN	91.4%	0.89	0.88

As can be seen, the neural network achieved an accuracy of 91.4%. This performance is higher than the average of traditional risk scales, confirming that deep learning better captures the nonlinear interactions of biomarkers.

3.2 Analysis of Predictive Capacity (AUC-ROC)

The discriminatory power of the winning model was validated using ROC curve analysis. The AUC value of 0.89 indicates excellent robustness in distinguishing between healthy and at-risk patients. The high sensitivity (0.88) is particularly relevant in the public health context, as it minimizes false negatives, allowing for timely intervention in patients who might otherwise be missed by the reactive system.

IV. CONCLUSION

This research demonstrates the feasibility and effectiveness of integrating cloud computing architectures with deep learning algorithms for the early detection of high blood pressure. It was confirmed that the implementation of intelligent models overcomes the limitations of traditional linear statistical methods. The Multilinear Logical Network (MLP) achieved an accuracy of 91.4% and an AUC-ROC of 0.89.

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