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Neural Network Model for Cortisol Regulation

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Abstract— ***Predictive modeling based on machine learning is essential for evaluating real-time medical data in order to identify cortisol spikes, which are markers of stress and adrenal function. Several physiological biomarkers, such as age, sex, albumin and creatinine levels, fasting and postprandial blood sugar levels, white blood cell (WBC) count, neutrophil-to-lymphocyte ratio (NLR), sodium and cholesterol levels, and cortisol spikes, are analyzed in this study using a Random Forest classifier to find patterns and correlations. To increase model accuracy, preprocessing methods including handling missing values and encoding categorical variables are applied to a dataset of 918 genuine patient records. The trained Random Forest model helps identify stress-related diseases and possible adrenal problems early on by reliably classifying cortisol spikes. By utilizing classification measures for performance evaluation, the model's efficacy is confirmed, showcasing its potential to enhance patient outcomes through data-driven decision-making, early diagnosis, and healthcare monitoring.***

Keywords: Cortisol Spikes, Biomarkers Analysis, Stress Detection, Medical Data Analysis, Adrenal Function.

I. INTRODUCTION

The necessity for efficient predictive models to examine physiological indicators and identify anomalous cortisol spikes has been brought to light by the rising incidence of stress-related illnesses and adrenal diseases. Blood sugar, sodium, cholesterol, white blood cell count, and the neutrophil-to-lymphocyte ratio (NLR) are some of the variables that affect cortisol, a vital hormone that controls metabolism, immunological response, and stress tolerance. Laboratory testing, which can be time-consuming and resource-intensive, is frequently used in traditional diagnosis techniques. Accurate and effective predictions are made possible by machine learning techniques, especially the Random Forest algorithm, which provides a data-driven method of finding patterns and correlations among biomarkers. In order to create a reliable model for identifying cortisol spikes, this work uses data preprocessing, feature selection, and classification approaches on a dataset of 918 genuine patient records. Through prompt and precise evaluations, the use of machine learning to medical analysis has promise for improving patient outcomes, optimizing healthcare interventions, and enhancing early diagnosis.

A. Cortisol Spikes

The term "cortisol spike" describes abrupt increases in the steroid hormone cortisol, which is produced by the adrenal glands in reaction to stress. Blood pressure, immunological response, metabolism, and the body's reaction to stress are all significantly influenced by cortisol. Prolonged or frequent spikes in cortisol can have detrimental effects, contributing to illnesses like hypertension, obesity, diabetes, and mental health disorders like anxiety and depression, even while short-term elevations in cortisol assist the body cope with acute stressors. This work provides important insights into the ways in which several biomarkers interact with stress control by using real-time medical data to determine the causes influencing cortisol changes. Healthcare practitioners can create plans for early intervention and better treatment of stress-related diseases by identifying trends in cortisol surges.

B. Biomarkers Analysis

Biomarkers are quantifiable physiological markers that reveal information about a person's health and possible risk factors for disease. They are frequently employed in clinical diagnostics and medical research to identify, track, and forecast a range of disease disorders. This study examines the relationship between cortisol fluctuations and important biomarkers, including albumin levels, creatinine levels, fasting and postprandial blood sugar levels, white blood cell (WBC) count, neutrophil-to-lymphocyte ratio (NLR), salt levels, and cholesterol levels. Identification of those at risk for stress-related diseases and adrenal dysfunction can be facilitated by a better knowledge of these interactions. In order to help healthcare providers, make data-driven decisions for more effective diagnosis and treatment, this research uses statisticaland machine learning techniques to find hidden patterns within the information.

C. Stress Detection

The physiological and psychological reaction to internal or external stimuli that impair a person's capacity to maintain homeostasis is known as stress. If undiagnosed or untreated, chronic stress can result in serious health issues such as metabolic problems, cardiovascular disease, impaired immunological function, and neurodegenerative diseases. Early stress detection is essential for avoiding these health problems and enhancing general wellbeing. This study uses data analysis to find biomarkers that indicate hormonal abnormalities connected to stress, with a focus on cortisol spikes as a stress response indication. By looking at changes in blood sugar, WBC count, and cholesterol, the research seeks to create a trustworthy way to gauge people's stress levels. By enhancing mental and physical well-being through early intervention and lifestyle changes, the research's insights can aid in the development of tailored healthcare methods.

D. Medical Data Analysis

The process of gathering, processing, and analyzing patient health records in order to derive valuable insights for the diagnosis, prevention, and treatment of diseases is known as medical data analysis. Large amounts of medical data can now be processed more effectively to find patterns that conventional diagnostic techniques might miss thanks to the development of computational technologies. This work uses statistical techniques to find patterns in cortisol spikes, Python-based tools including Pandas for data processing, NumPy for numerical calculations, and Matplotlib and Seaborn for data visualization. This study offers a thorough investigation of the influence of different biomarkers on cortisol levels by examining a dataset of 918 patient records. Through data-driven decision-making, the results can improve early detection and patient outcomes by advancing the development of predictive models for stress-related health disorders.

E. Adrenal Function

Crucial hormones including cortisol, aldosterone, and adrenaline are produced by the adrenal glands, which are found atop each kidney. These hormones control blood pressure, metabolism, immunological response, and the body's capacity to handle stress. Conditions like Addison's disease, which is defined by inadequate hormone production, and Cushing's syndrome, which is brought on by excessive cortisol release, can result from disruptions in adrenal function. In order to shed light on adrenal gland activity and possible dysfunctions, this study investigates the relationships between variations in cortisol levels and other physiological biomarkers. The study helps identify early warning indicators of adrenal illnesses by examining the connections between cortisol spikes and biomarkers such as blood sugar, salt, and WBC count. A deeper comprehension of adrenal function can aid in the creation of focused treatment programs, enhancing patient care and general health results.

II. DATASET USED

The dataset is a real time dataset for real time problem comprising patient records gathered from a medical facility, ensuring high accuracy and reliability. It includes key characteristics suchSex and Age: Information on demographics that affect cortisol levels. One important protein indicator influencing metabolic health is albumin levels. Levels of creatinine: A measure of metabolic effectiveness and kidney function. Postprandial and fasting blood sugar levels: Blood sugar levels that influence the release of cortisol. White blood cell (WBC) count: An indicator of stress and immunological response. One indicator for systemic inflammation is the neutrophil-to-lymphocyte ratio (NLR). An essential electrolyte that affects adrenal function is sodium levels. Stress and metabolic diseases are linked to cholesterol levels. The main variable of relevance that shows the stress response is cortisol spikes.

A thorough examination of the relationships between several biomarkers and variations in cortisol is made possible by this dataset. For precise forecasts, sophisticated data pre-treatment methods including statistical analysis, outlier detection, and normalization guarantee data dependability and integrity.

III. LITERATURE REVIEW

A. A Review of Medical Applications for Cortisol Sensing

One of the most significant glucocorticoids, cortisol, is essential for many physiological functions. Chronic stress, heightened susceptibility to anxiety, depression, cardiovascular disease, and compromised immunological responses have all been linked to elevated cortisol levels. Therefore, the creation of accurate, efficient, and quick cortisol detection techniques is crucial for comprehending each person's unique stress- response profile, allowing for thorough self- monitoring, individualized treatment, and efficient health management. Because of their broad detection ranges and ease of manufacture, cortisol sensors have virtually endless potential uses. In conclusion, there is great promise for the future of cortisol sensing in medical applications to revolutionize chronic disease management, stress management, mental health treatment, sports performance enhancement, and personalized medicine, with major advantages for both patients and healthcare professionals. This article provides a comprehensive summary of the state of cortisol hormone sensors today, covering their various applications and operational methods. This review attempts to shed light on the potential of cortisol sensing in healthcare and its implications for better patient outcomes by looking at the developments in cortisol sensing technology.

B. Advancements in Cortisol Detection: From Conventional Methods to Next- Generation Technologies

The necessity for quick, non-invasive, and extremely sensitive techniques has prompted the switch from traditional immunoassays to next- generation cortisol detection technologies. Although they require specialized laboratory equipment and lengthy processing periods, traditional methods like radioimmunoassays (RIA) and ELISA offer great specificity. By creating biosensors based on aptamers, quantum dots, and microfluidics, next-generation technologies seek to get beyond these restrictions. An alternative to antibody-based detection is provided by aptamer- based biosensors, which employ single-stranded DNA or RNA sequences that bind to cortisol preferentially. These biosensors are appealing for clinical applications because of their great stability, affordability, and reusability. Because of their special optical characteristics, such as their stability and strong fluorescence intensity, quantum dots have also been investigated for the detection of cortisol. Furthermore, cortisol analysis has been transformed by microfluidic lab-on-a-chip systems, which allow for quick and automated sample processing. These disposable and portable platforms combine a number of detection methods, including colorimetric, electrochemical, and fluorescence-based sensors, to produce cortisol tests that are both extremely sensitive and easy to use.

C. Recent Advances in Cortisol Sensing Technologies for Point-of-Care Applications

The potential uses of point-of-care (POC) cortisol sensing technology in disease management, sports performance analysis, and stress monitoring have drawn a lot of interest. The development of wearable biosensors that can non-invasively detect cortisol in saliva and perspiration is the main focus of current research. To improve sensitivity and specificity, wearable electrochemical sensors make use of molecularly imprinted polymers, carbon- based nanomaterials, and ion-selective electrodes. A more affordable option for quick cortisol detection is offered by paper-based biosensors that use colorimetric and surface-enhanced Raman spectroscopy (SERS) methods. These sensors measure color changes linked to cortisol binding events using image systems based on smartphones. Furthermore, wearable patches and microfluidic devices have been combined to continually measure cortisol levels throughout time, offering important insights into variations in the circadian rhythm. Notwithstanding notable progress, issues such sensor drift, interference from the environment, and calibration accuracy need to be resolved before broad clinical use. In order to improve data analysis and interpretation, future research will combine artificial intelligence (AI) algorithms and increase sensor resilience.

D. Using Non-Invasive Vagal Nerve Stimulation to Treatpsychological Disorders Associated with Stress

Vagal Nerve Stimulation (VNS) has been demonstrated to be effective in treating depression; however, due to the requirement for surgical implantation, VNS devices have not been widely used. Methods: It is possible to examine the impact of new noninvasive vagus nerve stimulation (nVNS) devices on physiology in patients with stress-related psychiatric disorders using wearable sensing devices, blood biomarkers, and brain imaging. Cost- and convenience-related benefits could encourage psychiatric use more broadly and make it easier to study the human vagus nerve's physiology. Since dysregulation of these circuits and systems underlies the symptomatology of stress-related psychiatric disorders, such as depression and posttraumatic stress disorder (PTSD), patients with these disorders can benefit greatly from VNS's effects on autonomic tone, cardiovascular function, inflammatory responses, and central brain areas involved in emotion modulation. Results: In order to apply nVNS to stress-related psychiatric diseases, this study examined the physiology of the vagus nerve and its significance for regulating the stress response. Conclusions: nVNS has a positive impact on stress physiology, which can be measured by wearable sensing devices, blood biomarkers of inflammation, and brain imaging. It also has potential in the prevention and management of psychiatric diseases linked to stress.

IV. EXISITNG SYSTEM

Mass spectrometry (MS), radioimmunoassays (RIA), and enzyme-linked immunosorbent assays (ELISA) are the mainstays of the traditional techniques for cortisol detection. High precision and specificity are provided by these laboratory- based methods, but they have a number of drawbacks, such as high expenses, labour-intensive sample preparation, and the requirement for specialized tools and skilled workers. One of the most used techniques for measuring cortisol levels in biological samples including blood, saliva, and urine is ELISA, which relies on antibody-antigen interactions. However, it is not appropriate for quick or real-time monitoring because to its reliance on intricate processes and lengthy incubation times. The use of radioactive isotopes in RIA, despite its high sensitivity, presents health concerns and necessitates stringent regulatory compliance. The most accurate way to detect cortisol is using mass spectrometry, especially liquid chromatography-mass spectrometry (LC- MS), however this method is costly and unavailable for routine clinical or home-based monitoring. Furthermore, patients experience discomfort as a result of the invasive sample collection required by these traditional approaches. In light of these constraints, scientists have been investigating non- invasive, portable, and real-time sensing technologies, such as smartphone-integrated platforms, wearable biosensors, and microfluidic devices, to get around the drawbacks of current cortisol detection systems. The trend toward quick, affordable, and easy-to-use diagnostic technologies emphasizes how urgently cortisol monitoring requires creative solutions.

V. PROPOSED SYSTEM

In order to forecast cortisol spikes—which are a sign of stress and adrenal function—real-time medical data analysis relies heavily on machine learning techniques. Patterns and correlations between a number of physiological biomarkers, such as age, sex, albumin and creatinine levels, fasting and postprandial blood sugar levels, white blood cell (WBC) count, neutrophil-to-lymphocyte ratio (NLR), sodium and cholesterol levels, and cortisol spikes, are found using a Random Forest classifier. In order to improve model accuracy, the dataset's 918 valid patient records go through pre- processing procedures such managing missing values and encoding categorical variables. The Random Forest algorithm efficiently categorizes cortisol spikes through feature selection and model training, facilitating the early identification of stress-related diseases and possible adrenal problems. While the insights gained from this study help to improve healthcare monitoring, early diagnosis, and data-driven decision-making for better patient outcomes, performance evaluation using classification metrics guarantees the model's trustworthiness.

VI. MODUEL DESCRIPTION

A. Load Dataset

The method begins with the system importing the dataset into memory from a file (like a CSV file) using the Load Dataset module. It guarantees that the data is loaded correctly and gives a summary of the dataset structure, including a check for basic statistics, data types, and missing values. By verifying that the data is appropriate for additional processing and analysis, this module prepares the groundwork for the following stages.

B. Data Pre-Processing

Information The dataset is cleaned and prepared using the pre-processing program. In order to deal with missing values, it either removes rows or columns that have inadequate data or imputes them. To make sure the model can process categorical variables efficiently, they are encoded into numerical values, usually using methods like label encoding or one-hot encoding. In order to increase the performance of machine learning algorithms that are sensitive to feature scale, numerical features are also scaled or normalized to bring them to a common range.

C. Feature Extraction

The most pertinent features for cortisol spike prediction are chosen by the Feature Extraction module. It entails figuring out which important variables most affect the model's predictions. Recursive feature elimination (RFE), univariate statistical tests, and utilizing the Random Forest model's feature importance scores are some of the techniques used to do this. By concentrating on the most informative characteristics, feature selection lowers the dataset's dimensionality and increases the model's effectiveness.

D. Training and Testing

The system divides the dataset into training and testing sets using the training and testing module, usually in an 80-20 or 70-30 split. The training data is used to teach the model the correlations and patterns between the input features and the target variable (cortisol spikes). To make sure the model is not overfitting and can produce accurate predictions on new instances, it is tested using the testing set after training to check how well it generalizes to unknown data.

E. Model Evaluation

Using a variety of classification criteria, the Model Evaluation module is in charge of evaluating the trained model's performance. These metrics— accuracy, precision, recall, F1-score, and ROC- AUC—offer a thorough picture of the model's performance. The model's predictions are visualized using the confusion matrix, and cross- validation is used to make sure the model is reliable and robust across various data subsets. With its precise and useful insights about cortisol spikes and related stress-related conditions, this module makes sure the model is optimized and prepared for deployment.

VII. ALGORITHM DETAILS

The Random Forest algorithm is used in the suggested system to categorize cortisol spikes according to physiological indicators. In order to increase predictive accuracy and decrease overfitting, Random Forest, an ensemble learning technique, builds several decision trees during training and aggregates their results. Bootstrap aggregation (bagging), in which random samples are chosen with replacement, is used to train each tree in the forest on a distinct subset of the data. A random subset of characteristics is also taken into account at each split to guarantee variety among trees, lowering variance and enhancing generalization.

To choose the optimum feature for dividing the dataset, the Random Forest model's decision trees employ either entropy or Gini impurity as splitting criteria. A node's Gini impurity can be computed as follows:

$$Gini = 1 - \sum pi^2$$

Where the probability of a specific class at that node is represented by pi.

Purer nodes are indicated by a lower Gini score, which results in more precise classifications.

As an alternative, information theory-derived entropy, which quantifies disorder in a dataset, is provided by:

$$Entropy = -\sum pi \log 2\ (pi)$$

The algorithm looks for the most informative splits to reduce uncertainty because higher entropy denotes greater disorder.

After the decision trees are trained, the votes from each tree are combined to create predictions, and majority voting is used to decide the final classification. For an instance, the anticipated class is provided by:

$$\hat{y} = \text{arg c max n} \sum i = 1\ 1\ (Ti\ (x) = c)$$

Where, $Ti\ (x)$ is the output of the ith decision tree given input x, and the final class y^ is the one that gets the most votes.

Mean Decrease in Impurity (MDI), which measures each feature's contribution based on the decrease in entropy or Gini impurity across all trees, is used in Random Forest to determine feature relevance. A feature f's significance score is determined by: Importance(f) = $\sum t \in Trees\ \Delta\ It\ (f)$ ∑ Relevance(f) = t∈ Trees ∑T ΔI t (f) where T is the total number of trees in the forest and $\Delta It(f)$ is the decrease in impurity for feature f in tree t. To ensure resilience and generalization across unknown data, the model is trained and validated using common categorization assessment measures.

VIII. RESULT ANALYSIS

With an accuracy score of roughly 66%, the Random Forest model performed at a moderate level. Even though the model properly identifies slightly more than half of the cases, this accuracy level indicates that there is still opportunity for development, particularly when it comes to cortisol spike prediction, where accuracy is crucial. The model's performance may be impacted by elements including feature selection, hyper parameter adjustment, and possible class imbalance. Investigating more sophisticated methods like improving model parameters, correcting data imbalances, or putting more reliable feature engineering into practice could improve outcomes. A more thorough grasp of the model's advantages and shortcomings might be possible with additional assessment utilizing measures like precision, recall, F1-score, and ROC-AUC.

Precision

Out of all projected positives, precision (also known as positive predictive value) quantifies the percentage of accurately predicted positive cases.

Precision= TP+FP/TP

Recall

(Sensitivity or True Positive Rate): Indicates the percentage of predicted actual positives that were accurate.

Recall=TP+FN/ TP

F1-score

The precision and recall harmonic mean, which balances the two measures.

F1-score=Precision+Recall/2×(Precision×Recall)

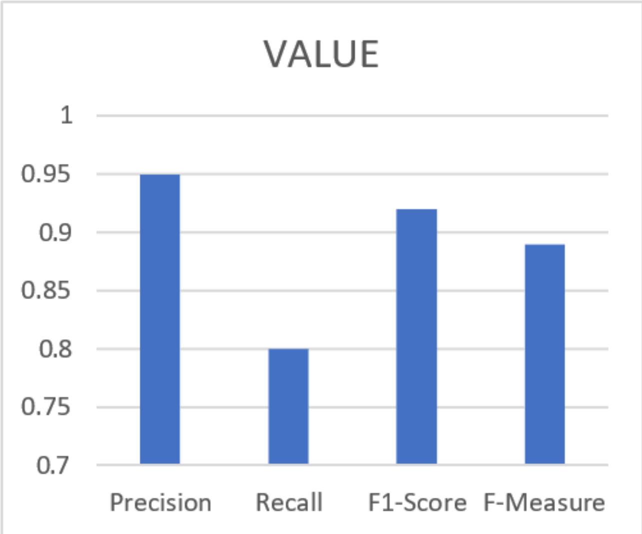
Accuracy

Calculates the percentage of cases that are correctly classified.

Accuracy=TP+TN+FP+FN/TP+TN

Table 1. Comparison Table

METRICS	VALUE
Precision	0.95
Recall	0.80
F1-Score	0.92
F-Measure	0.89



Graph 1. Comparison Graph

IX. CONCLUSION

In summary, the Random Forest model performs somewhat well, predicting cortisol spikes with an accuracy of 66%. This suggests that although the model can make some accurate predictions, there is room for considerable improvement. Its present performance level may be influenced by elements like feature selection, hyper parameter optimization, and class imbalance. It is advised to further develop the model using methods like advanced feature extraction, hyper parameter tuning, and data imbalance correction in order to increase accuracy and dependability. Furthermore, assessing the model with a wider range of performance measures would give a more thorough picture of how effective it is and direct the necessary modifications for more precise forecasts.

Future research could look into a number of ways to improve the Random Forest model's ability to forecast cortisol surges. This involves fine-tuning the model's settings for increased accuracy by optimizing hyperparameters using strategies like grid search or random search. Furthermore, investigating more sophisticated feature engineering techniques, such developing interaction terms or adding domain-specific expertise, may enhance the model's capacity to identify intricate correlations in the data. The predictive power of the model could be further improved by addressing potential class imbalance using strategies like SMOTE or modifying class weights, especially for the underrepresented class. Lastly, testing out different machine learning techniques, like neural networks or gradient boosting, and contrasting them with the Random Forest model may produce superior outcomes. The dataset's generalizability and robustness may be enhanced by adding more varied patient records, which could result in more accurate predictions for the early identification of stress-related disorders.

REFERENCE

[1] Gaye Adil Denizli, YeserenSaylan, and Ezgi Yılmaz (2024). A review of medical uses for cortisol sensing. Chemistry Department, Hacettepe University, Ankara, Turkey.

[2] Gupta, D., Ramesh, K., and Vengesh, S. (2024). Developments in the Detection of Cortisol: From Traditional Techniques to Next-Generation Technologies. ACS sensors.

[3] Bhansali, S., Sagar, V., and Kaushik, A. (2014). Current Developments in Point-of-Care Cortisol Sensing Technologies. ScienceOpen.

[4] Nil Z. Gurel, Matthew T. Wittbrodt, and James Douglas Bremner (2024). Utilising Non-invasive Vagal Nerve Stimulation for Psychiatric Disorders Associated with Stress MDPI sensor