Stress Level Diagnosis Using Iot And Machine Learning

***Abstract*—In response to escalating health concerns, this research pioneers a novel approach to stress diagnosis, leveraging the synergy between Internet of Things (IoT) and machine learning (ML). The "Stress.lysis" dataset, encompassing critical parameters such as humidity, temperature, step count, and stress levels, serves as the cornerstone of our investigation. Through the deployment of three distinct sensors—humidity, step count, and temperature—our system captures real-time physiological data, thus laying the groundwork for comprehensive stress assessment. Our methodology integrates cutting-edge ML algorithms, including Naive Bayes, k-nearest neighbor (KNN), logistic regression, and support vector machine (SVM), to analyze the acquired data. These algorithms scrutinize the intricate interplay between physiological metrics and stress patterns, enabling the classification of stress into three distinct levels: low, medium, and high. This analytical process underscores a nuanced understanding of stress dynamics, fostering improved health management strategies. Our research not only contributes to the evolution of stress diagnostics but also holds promise for enhancing healthcare management practices through data-driven insights.**

Keywords — Stress Diagnosis, Internet of Things, Machine Learning, Sensor Data, stress.lysis dataset, Naive Bayes, k-Nearest Neighbors, Logistic Regression, SVM, Stress Classification.

I. INTRODUCTION

In an age of increasing health anxiety, this research brings to the fore many diagnostics challenges involving the Internet of Things (IoT) and machine learning (ML). The "Stress. lysis" file is basic and contains the main parameters - humidity, temperature, number of steps and stress level. Using three sensors that monitor temperature, step count, and humidity, the program uses a variety of machine learning algorithms, including Naive Bayes, K- nearest neighbour (KNN), logistic regression and SVM. This new approach aims to revolutionize stress assessment by combining physical activity measurements with advanced techniques, providing a better understanding of stress patterns to improve health management and related strategies.

Shortcomings:

Limited Sensor Range: The project may encounter limitations in sensor range, which may affect the ability to capture environmental information. If the user moves out of range of the sensor, the accuracy of the height measurement will be affected.

Power Consumption: The system relies on many sensors and continuous data processing results in increased power consumption. This can create difficulties, especially if the demo product or final product is intended to be used for a long time without paying too much money.

Algorithmic Sensitivity: Machine learning algorithms, when implemented well, can show sensitivity to outliers or unusual patterns in data, which can occasionally lead to misclassification of depression. It can be difficult to Finetune algorithms to address different users and physiological responses.

Cost and Accessibility: The use of IoT devices and machine learning algorithms can have significant costs that may limit widespread access. Addressing cost issues and ensuring affordability is critical to the project's scalability and societal impact.

Machine Learning Considerations: Machine learning implementation may introduce additional complexity.

Addressing resource-intensive nature and potential computational requirements is essential for practical deployment.

II. METHODOLOGY

A. Process

The technique by which the stress level diagnosis system functions is carefully thought out, and it starts with gathering important information from the "stress-lysis" dataset. This dataset forms the basis of our project's input by capturing important factors including temperature, step count, humidity, and stress levels. The next phase is the installation of three different sensors: a humidity sensor to measure perspiration patterns, a step count sensor to measure levels of physical activity, and a temperature sensor to track body temperature. Together, these sensors record physiological data in real time.

The technology feeds data into an advanced group of machine learning algorithms after it has been acquired. The selected algorithms thoroughly examine the input data, including Naive Bayes, SVM, Logistic Regression, and k-nearest Neighbours (KNN). These algorithms' decision-making process leads to the division of stress levels into three groups: low, middle, and high. This phase encompasses complex calculation in addition to a thorough comprehension of the interaction between physiological data and stress patterns.

A small demo device is designed to show how this stress level diagnosis system might be used in real life. This gadget acts as a physical embodiment of the working model, demonstrating how the combination of machine learning algorithms and sensors results in the real-time evaluation of an individual's stress level. The. project's innovation lies not only in its analytical depth but also in its ability to bridge the gap between data science and tangible, user-friendly applications, thereby contributing to advancements in stress monitoring and healthcare management.

B. Block Diagram

The stress level diagnosis system's smooth workflow is explained by the block diagram. Gather physiological data in real-time starting with the three most important sensors: temperature, step count, and humidity. A strong collection of machine learning algorithms, such as Naive Bayes, k-Nearest Neighbors (KNN), Logistic Regression and SVM, are then fed this data. After the input is carefully processed by the algorithms, the stress levels are divided into three categories: low, middle, and high. The process's conclusion is represented by arrows that highlight the information flow and demonstrate how well sensor inputs and the machine learning framework work together to accurately measure a person's stress level.

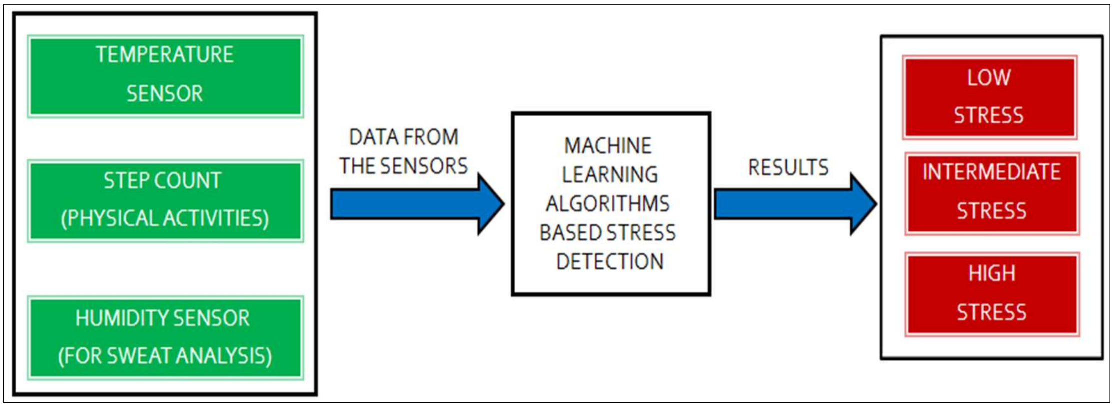


Fig. 1. Block Diagram Of the system's workflow

C. Tools used

The Arduino UNO microcontroller is the main instrument guiding the creation and integration of our stress level diagnostic system. The project's computational core is this adaptable microcontroller, which makes it easier to program and coordinate different modules. The temperature, step count, and humidity sensors are individually programmed using the Arduino UNO, which facilitates data interchange and communication.

Furthermore, the Arduino UNO is essential to the implementation of the chosen machine learning algorithms, which include SVM, Logistic Regression, k-nearest Neighbours (KNN), and Naive Bayes. These algorithms may be coordinated thanks to their flexibility and ease of integration, which permits a thorough examination of the physiological data gathered from the sensors.

The Arduino UNO provides a user-friendly example of stress assessment in many settings by showcasing the convergence of sensor data and machine learning algorithms through its intuitive interface.

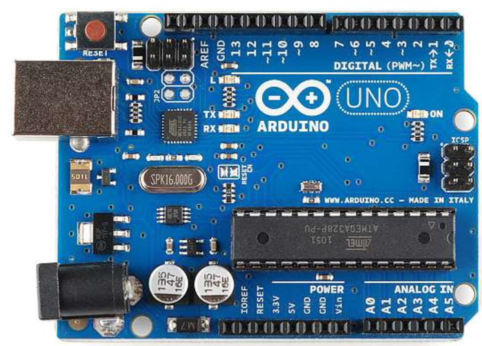


Fig. 2. Arduino Microcontroller

D. Flow Of Control

The Arduino manages the control flow of the diagnostic system. Sensor data such as humidity, step count, and temperature, are gathered and handled separately. Then, the machine learning algorithms are used one after the other, and the classification of stress levels is affected by the outcomes. The control flow shows how commands move through each module, guaranteeing a methodical and feedback-driven approach to the process of stress assessment.

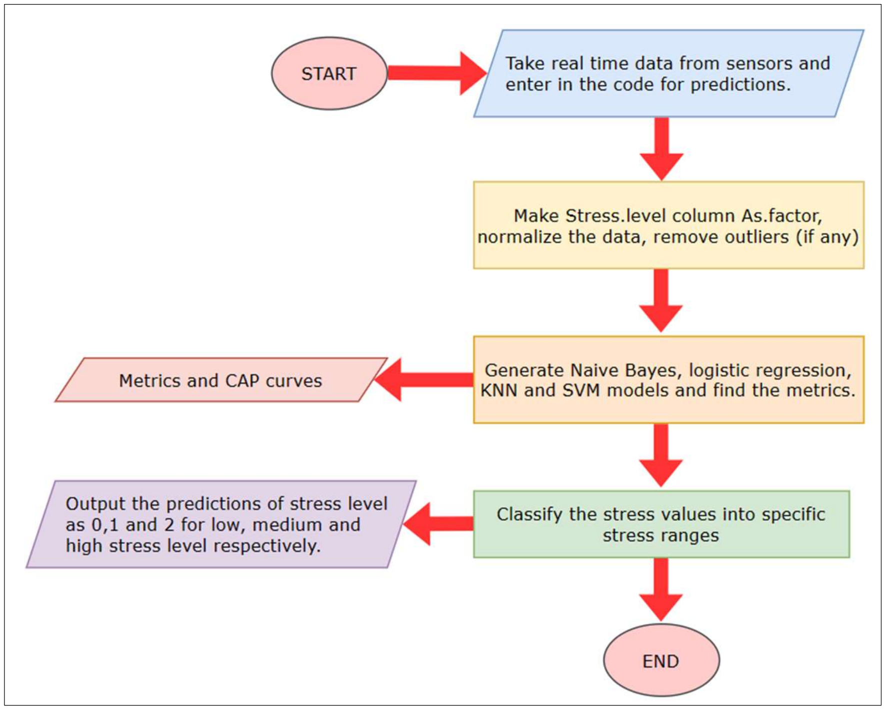


Fig. 3. General Flow of Control

E. *Algorithm's Flow Of Control*

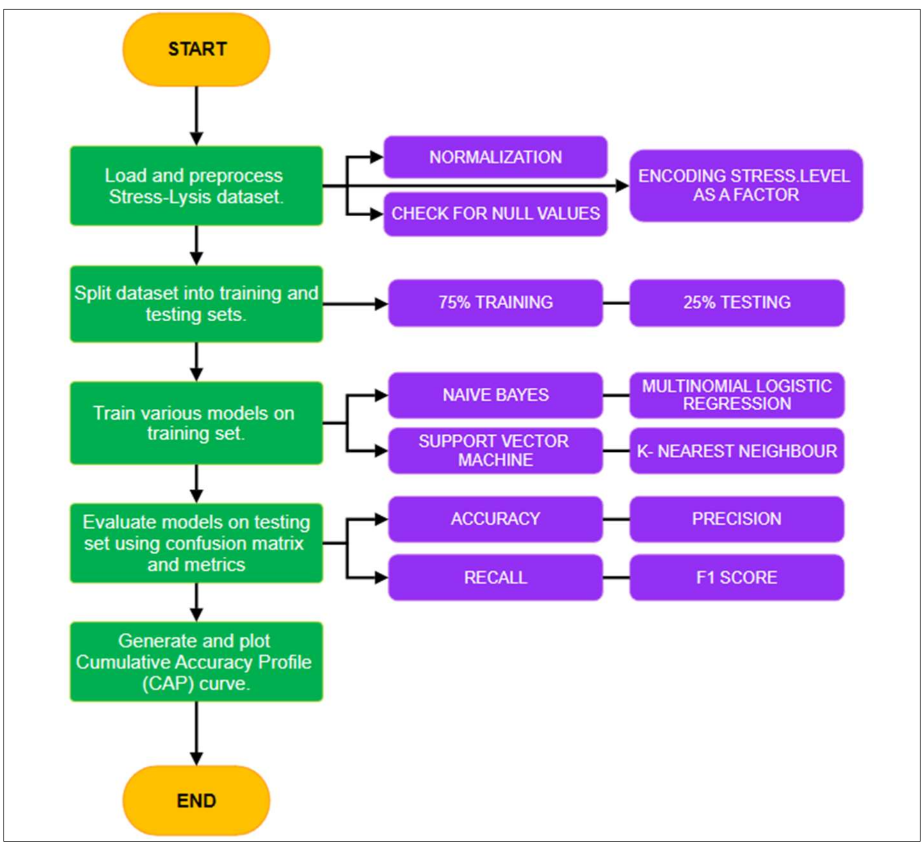


Fig. 4. Flow Of Control of Algorithms

III. RESULTS AND DISCUSSION

This section contains the results of our experiments that we ran on the stress level diagnosis system to assess its practicality. To confirm that the stress level diagnosis system could reliably determine stress levels from a variety of physiological data, it was put through extensive testing.

Output:

IOT:

The real-time capability of the stress level diagnosis system was demonstrated through the use of IOT, which acted as a practical application of the system. Visitors were able to observe the methodical assimilation of sensor data and the machine learning algorithms' decision-making process, offering a concrete illustration of stress evaluation in regulated environments.

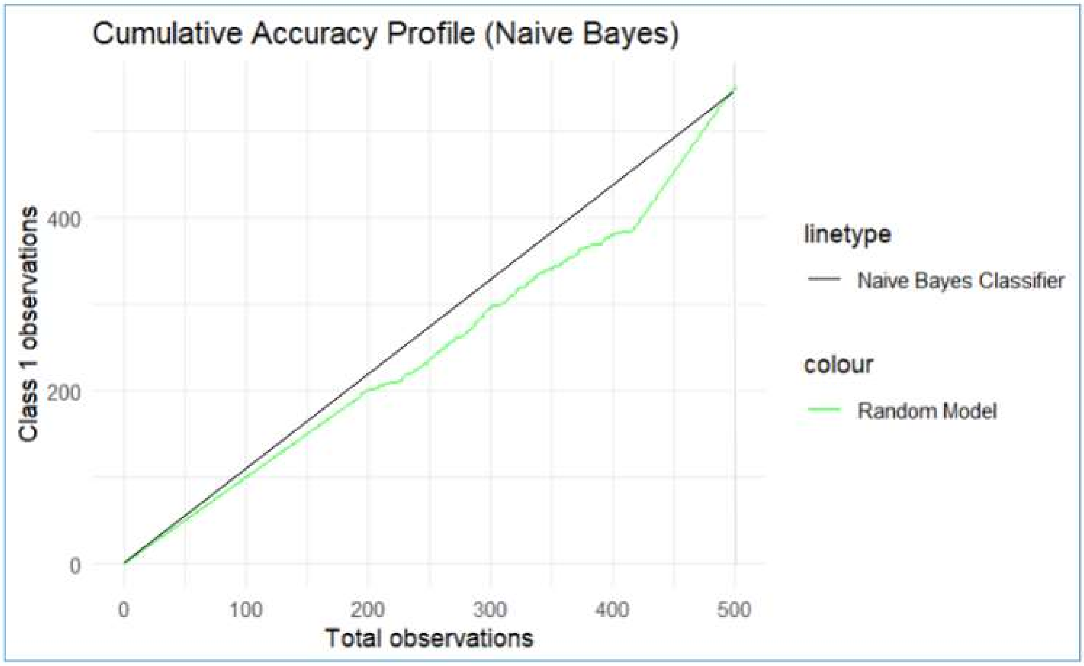


Fig. 5. CAP Curve for Naive bayes

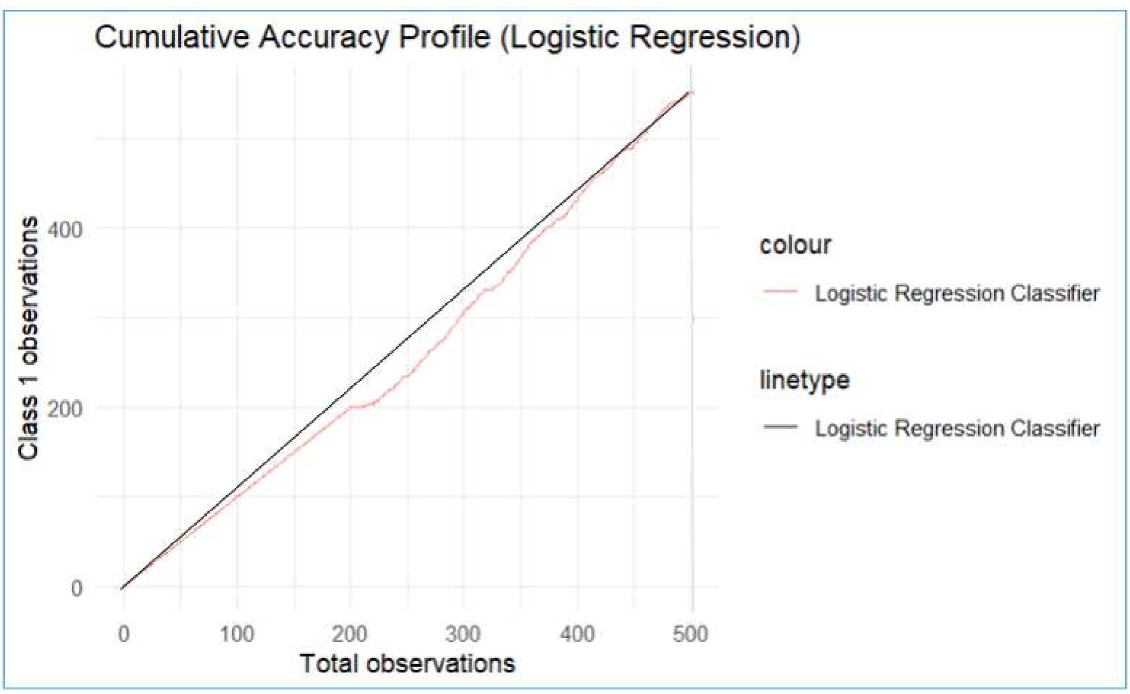


Fig. 6. CAP Curve for Logistic regression

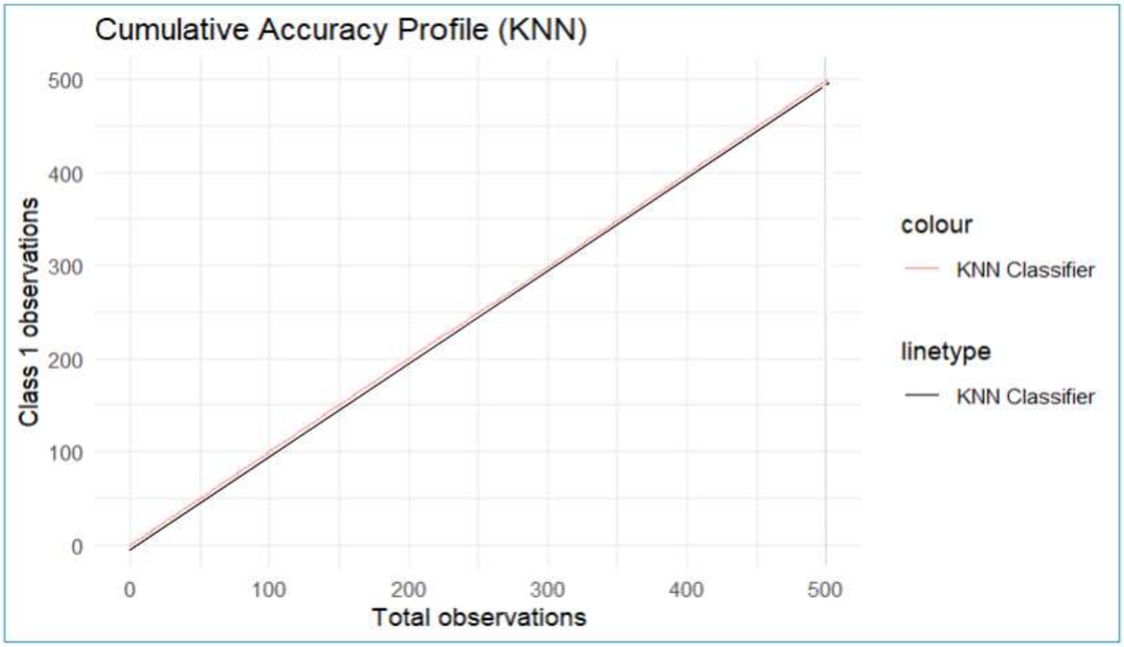


Fig. 7. CAP Curve for KNN

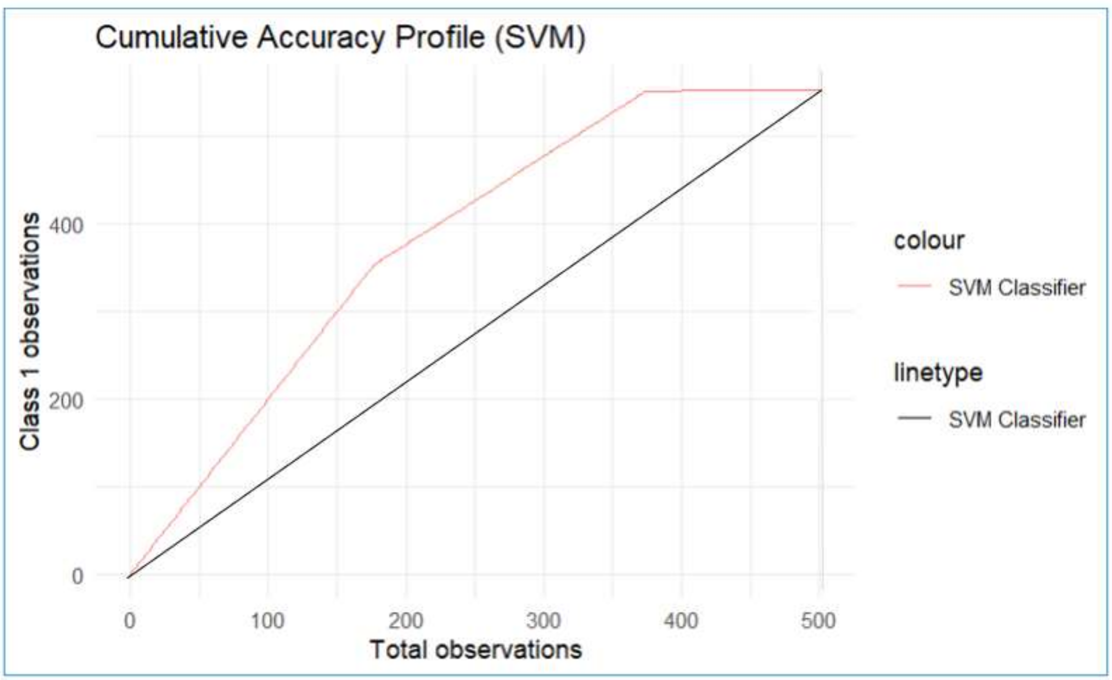
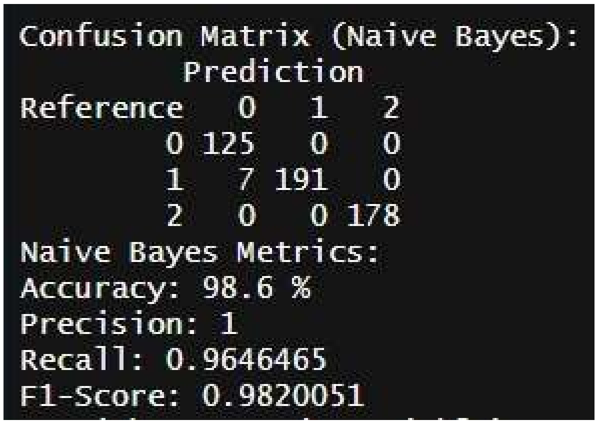


Fig. 8. CAP Curve for SVM



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Confusion Matrix (Naive Bayes):
          Prediction
Reference   0   1   2
        0 125   0   0
        1   7 191   0
        2   0   0 178
Naive Bayes Metrics:
Accuracy: 98.6 %
Precision: 1
Recall: 0.9646465
F1-Score: 0.9820051
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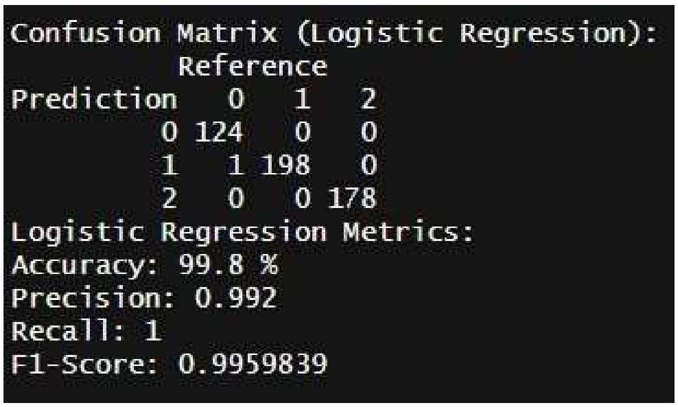
Fig. 9. Confusion Matrix for Naïve Bayes



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Confusion Matrix (Logistic Regression):
          Reference
Prediction   0   1   2
         0 124   0   0
         1   1 198   0
         2   0   0 178
Logistic Regression Metrics:
Accuracy: 99.8 %
Precision: 0.992
Recall: 1
F1-Score: 0.9959839
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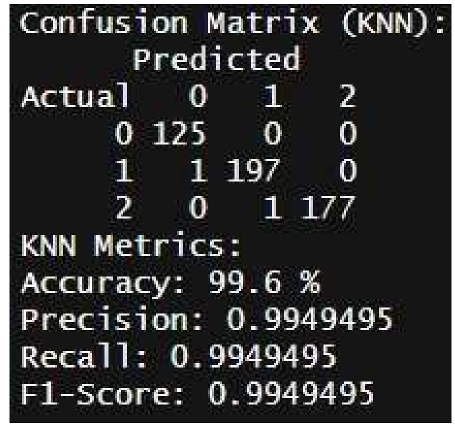
Fig. 10. Confusion Matrix for Logistic Regression



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Confusion Matrix (KNN):
      Predicted
Actual   0   1   2
     0 125   0   0
     1   1 197   0
     2   0   1 177
KNN Metrics:
Accuracy: 99.6 %
Precision: 0.9949495
Recall: 0.9949495
F1-Score: 0.9949495
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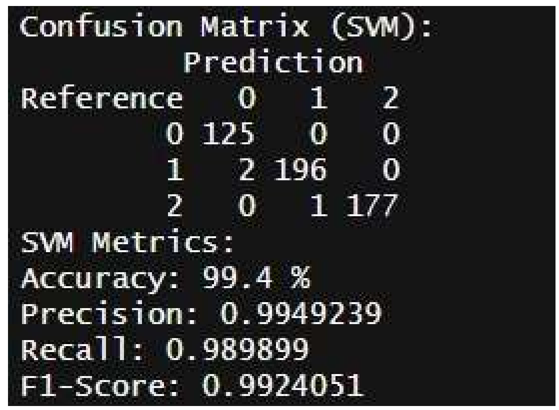
Fig. 11. Confusion Matrix for KNN



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Confusion Matrix (SVM):
          Prediction
Reference   0   1   2
        0 125   0   0
        1   2 196   0
        2   0   1 177
SVM Metrics:
Accuracy: 99.4 %
Precision: 0.9949239
Recall: 0.989899
F1-Score: 0.9924051
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Fig. 12. Confusion Matrix for SVM

Discussion:

The stress level diagnosis system performed well in stress categorization, demonstrating flexibility in response to various inputs and producing precise outcomes. The modules' sequential operation made sure that the stress assessment procedure was organized and effective. The project's novelty and usefulness were clearly represented by the demo gadget, which also highlighted the technology's potential for practical use.

In summary, the stress level diagnosis system has demonstrated encouraging outcomes in stress assessment through thorough testing and validation, highlighting its potential as a useful tool for proactive health monitoring and intervention.

Comparative Analysis:

Results found in our model:

TABLE I. METRICES OF ALL ALGORITHMS

METRIC	NAIVE BAYES	LOGISTIC REGRESSION	KNN	SVM
ACCURACY	98.6	99.8	99.6	99.4
PRECISION	1	0.992	0.994	0.994
RECALL	0.964	1	0.994	0.989
F1 SCORE	0.982	0.995	0.994	0.992

When it came to identifying stress levels, the machine learning algorithms Naive Bayes, k-Nearest Neighbours (KNN), Logistic Regression and SVM performed admirably. The accuracy of logistic regression was the most. The system successfully classified stress into low, middle, and high levels across a variety of scenarios and datasets, demonstrating its versatility and dependability in diverse circumstances.

TABLE II. COMPARISON BETWEEN VARIOUS RESEARCHES [8]

RESEARCH	SENSORS	STRESS FACTORS	ACCURACY (%)	COST	SYSTEM COMPLEXITY	ENERGY CONSUMED
[7] Wearable Physiological Sensors Reflect Mental Stress State in Office- Like Situations	ECG, Respiration, ESR	Puzzles, Calculations, Memory Tasks	74.5	211	Moderate	Moderate
[9] DeStress: Mobile and Remote Stress Monitoring, Alleviation, and Management Platform	Photoplethysmogram	Daily Activities	Unavailable	180	Moderate	Moderate
[10] Continuous Inference of Psychological Stress from Sensory Measurements Collected in the Natural Environment	Skin Temperature, Accelerometer, ECG, GSR, Respiration	Public Speaking, Maths	90.2	175	Complex	Moderate
[11] Wearable System for Stress Monitoring of Firefighters in Special Missions	HR, Humidity, Temperature	Physical Activity	85.7	100	Highly Complex	High
[12] Stress Detection in Computer Users Based on Digital Signal Processing of Non invasive Physiological Variables	Pupil Diameter, Skin Temperature, GSR, Blood Volume Pulse	Stroop Colour Test	90.1	100	Complex	Moderate
[13] Diagnosis and Biofeedback System for Stress	Finger Temperature	Verbal, Math	80.0	35	Moderate	Moderate
[14] Using Heart Rate Monitors to Detect Mental Stress	Respiration, GSR, Heart Rate Monitor	Mental Arithmetic, Stroop Colour Test	83.0	200	Complex	Moderate
[15] Keep the Stress Away with SoDA: Stress Detection and Alleviation System	ECG, BP, GSR, ESP, BO	Memory Game, Fly Sound, IAPS, Ice Test	95.8	200	Complex	High
[16], [17] A Smart Sensor in the IoMT for Stress Level Detection, I-Stress: A Stress Monitoring System through the IoT	Temperature Senor, Humidity Sensor, Accelerometer Sensor	Physical activity	95.6	25	Less Complex	Moderate
Stress Level Diagnosis Using IOT and Machine Learning	**Temperature and Humidity Sensor**	**Physical activity**	**98.6 to 99.8**	**25**	**Less Complex, high range of sample size**	**Low**

For example, the comparison between the first research paper and the research that we performed, their accuracy came out to be 74.5 % whereas our accuracy ranged between 98.3-99.7%. Coming to the cost comparison, ours was on a lower side. Their energy consumed was moderate while ours came out to be on the lower side. Our complexity was lesser, with higher range of sample size whereas theirs was moderate.

IV. CONCLUSION

In conclusion, this study presents the Stress Level Diagnosis System, a novel approach that successfully assesses and categorizes stress levels by leveraging machine learning (ML) and the Internet of Things (IoT). The suggested method has proven to be successful in precisely determining stress levels in a range of circumstances through rigorous testing and analysis, providing insightful information about people's psychological health.

The Stress Level Diagnosis System's findings suggest that it can completely change the field of stress management and monitoring. The system ensures a precise classification of stress into low, middle, and high levels by smoothly integrating physiological data from sensors measuring temperature, step count, and humidity. This not only makes early intervention possible, but it also gives people and medical professionals useful information for proactive stress reduction.

V. FUTURE SCOPE

For enhancement and future development, several avenues could be explored to make the system more advanced, robust, and industry ready.

Integration of Sensors:

Adding sophisticated sensors for physiological data collection can improve stress assessment accuracy. Incorporating modern biosensors offers a deeper understanding of physiological reactions and expands the scope of stress assessment.

Improved Machine Learning Algorithms:

Investigating complex algorithms, such as ensemble techniques or advanced neural network topologies, can enhance stress classification accuracy across various datasets.

Enhanced Device Structure:

Strengthening the external framework of the diagnostic gadget ensures resilience in real-world situations. Using materials and structures that reduce the impact of vibrations or physical motions improves endurance and reliability.

Inbuilt Powering Solutions:

Incorporating an internal power source like a large-capacity Lithium-ion battery enhances system dependability and independence. Extended working duration ensures continuous monitoring and stress assessment without frequent recharging.

VI. ACKNOWLEDGEMENT

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