SmartStride: Revolutionising Treadmill Workouts with IoT and Machine Learning

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***Abstract*— This paper presents SmartStride, a novel smart treadmill system integrating Internet of Things technology and machine learning to personalise the user's running experience. The system utilises an ESP32 microcontroller housed in a custom 3D-printed case attached to the treadmill. Infrared sensors track the user's movement, and the collected data is transmitted to a mobile application designed using MIT App Inventor. The app leverages user-specific parameters like weight, height, and fitness goals to generate personalised run graphs and suggests workout plans via a machine-learning model. SmartStride addresses the growing demand for intelligent fitness equipment by offering a user-centric approach to treadmill workouts.**

Keywords*— *Smart Stride, Internet of Things technology, machine learning, user-specific parameters, personalised run graphs, fitness goals

I. INTRODUCTION

The desire for a healthier lifestyle has fueled a constant evolution in the fitness industry. From the rudimentary dumbbells of yesteryear to the high-tech exercise bikes of today, technology has continually reshaped how we approach our workouts. One area ripe for transformation is the traditional treadmill. While offering a convenient and efficient way to exercise, treadmills cannot often adapt to individual needs. This one-size-fits-all approach can lead to frustration, plateaus in progress, and ultimately, a decline in motivation.

The inability of traditional treadmills to personalise the workout experience stems from a lack of user data integration. These machines operate in isolation, offering pre-programmed settings that may not align with an individual's fitness goals, physical limitations, or running form. This disconnect between the user and machine hinders progress and can even lead to injuries.

However, the winds of change are blowing through the fitness landscape. The burgeoning field of smart technologies is poised to revolutionise exercise routines, transforming them from monotonous routines into personalised journeys towards peak performance. SmartStride stands at the forefront of this exciting movement. We envision a future where treadmills become intelligent companions, not just exercise equipment. By seamlessly integrating Internet of Things (IoT) technology and machine learning algorithms, SmartStride empowers users to unlock their full potential, one personalised stride at a time.

This paper delves into the innovative features of SmartStride, exploring how it addresses the limitations of traditional treadmills. We will examine the system architecture, the role of machine learning in generating personalised workout plans, and the real-time data analysis that fuels user progress. Through a detailed discussion of the hardware components and software functionalities, we will demonstrate how SmartStride bridges the gap between human potential and technological capability. Finally, we will explore the future directions for SmartStride, outlining our vision for even more sophisticated user interaction and a truly holistic fitness experience.

II. LITERATURE REVIEW

Numerous studies have delved into the realm of smart treadmill innovations, aiming to revolutionise traditional treadmill training methods and enhance the overall running experience. These endeavours encompass a wide array of objectives and methodologies, each contributing valuable insights to the field of fitness technology.

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Researchers have explored the concept of automatic speed adaptation treadmills, seeking to address the limitations of conventional treadmill training methods. Through a comparative analysis of different approaches, these studies aim to develop strategies for adapting treadmill speed based on the user's desired pace, thereby optimising training effectiveness and user experience.

Another area of focus lies in validating algorithms for running analysis using wearable IoT technology. Studies have aimed to assess the accuracy of inertial-based algorithms in quantifying ground contact time and swing time during running, employing methodologies that involve recruiting large cohorts of participants for treadmill-based testing while wearing IoT-enabled wearable devices.

Furthermore, research has been conducted on gait analysis for shoe recommendation using wearable IoT technology. By analysing gait patterns through inertial measurement unit (IMU) data, researchers aim to recommend suitable running shoes based on pronation and foot-strike location. Data collection from diverse cohorts of healthy individuals running on treadmills with wearable devices is crucial to these studies.

Comprehensive surveys have also been conducted to explore the landscape of wearable sensors and their applications in gait analysis. These surveys aim to review existing literature on wearable sensor technologies, data processing techniques, and applications in gait analysis for various purposes, ranging from rehabilitation to sports performance and shoe recommendation.

Moreover, comparative analyses have been undertaken to evaluate different types of self-paced treadmills for rehabilitation purposes. These studies seek to assess the effectiveness of various control systems used in self-paced treadmills, such as position-based control, inertial force-based control, and physiology-based control, by reviewing existing literature and analysing features and performance.

Additionally, efforts have been made to develop wearable gait analysis devices for running injury prevention. Researchers aim to create devices capable of accurately analysing a runner's gait patterns and providing real-time feedback to prevent injuries. The methodologies employed include designing and prototyping wearable devices, conducting validation studies to assess accuracy, and evaluating effectiveness in injury prevention.

[1] Hee Jin Park, 2015, investigates the concept of automatic speed adaptation treadmills, aiming to address the limitations of traditional treadmill training methods. The study aims to explore different methods of adapting treadmill speed based on the user's desired pace. The methodology she involves is a review of existing literature on automatic treadmill speed adaptation and a comparative analysis of different approaches.

[2] Fraser Young, 2021, focuses on validating an inertial-based contact and swing time algorithm for running analysis using a foot-mounted IoT-enabled wearable device. The objective is to assess the accuracy of the algorithm in quantifying ground contact time and swing time during running. The methodology includes recruiting a large cohort of participants to run on a treadmill while wearing the wearable device and comparing the algorithm's output with manually labelled reference standard data.

[3] Joao M.O. Passos, 2022, explores the use of wearable IoT technology for gait analysis and shoe recommendation. The objective is to develop an algorithm that analyses a runner's gait patterns using inertial measurement unit (IMU) data and recommends suitable running shoes based on pronation and foot-strike location. He used a methodology that involved data collection from a large cohort of healthy adults and adolescents running on a treadmill while wearing the wearable device.

[4] Chad O'Brien, 2022, provides a comprehensive survey of wearable sensors and their applications in gait analysis. The objective is to review existing literature on wearable sensor technologies, data processing techniques, and applications in gait analysis for various purposes, including rehabilitation, sports performance, and shoe recommendation. The methodology involves a systematic review of relevant studies and a synthesis of key findings.

[5] Shaolong Liu, 2020, compares different types of self-paced treadmills for rehabilitation purposes. The objective is to evaluate the effectiveness of various control systems used in self-paced treadmills, such as position-based control, inertial force-based control, gait parameter-based control, and physiology-based control. The methodology includes a review of existing literature on self-paced treadmills and a comparative analysis of their features and performance.

[6] Ravishankar Natarajan, 2022, introduces a wearable gait analysis device for running injury prevention. The objective is to develop a device that can accurately analyse a runner's gait patterns and provide real-time feedback to prevent injuries. The methodology involves designing and prototyping the wearable device, conducting validation studies to assess its accuracy, and evaluating its effectiveness in preventing running injuries.

III. PROPOSED SYSTEM

SmartStride introduces a ground-breaking approach to treadmill fitness by seamlessly integrating various technologies like IoT, Machine Learning, Cloud Computing and Mobile Applications. The system, centred around an ESP32 microcontroller, collects treadmill data, and communicates via Bluetooth Low Energy. Additionally, IR and gyroscope sensors enhance data accuracy. A user-friendly Mobile App serves as the control interface, facilitating interaction with backend systems and the IoT device. Through machine learning, specifically LSTM models, SmartStride analyses user data to craft personalised workout plans stored in a cloud-based database. Heart rate warning messages on the app screen during runs prioritise user safety, ensuring a holistic and personalised fitness experience. FastAPI ensures seamless data exchange, enhancing communication efficiency. Overall, SmartStride represents a significant leap in personalised fitness equipment, delivering tailored workout experiences and engaging users through its integrated ecosystem.

I. ARCHITECTURE

The architecture of SmartStride is designed to integrate IoT technology, a mobile app, machine learning, a database, and API calls to deliver a seamless and personalized fitness Experience.

1. IoT (ESP32)

The IoT aspect of SmartStride is facilitated by the ESP32 microcontroller, which acts as the central hub for collecting live data on the treadmill. These sensors capture vital information such as running speed, distance, and inclination. The ESP32 then communicates this data wirelessly over Bluetooth Low Energy (BLE) to the mobile app, ensuring seamless connectivity with other system components, as illustrated in **Figure 1.**

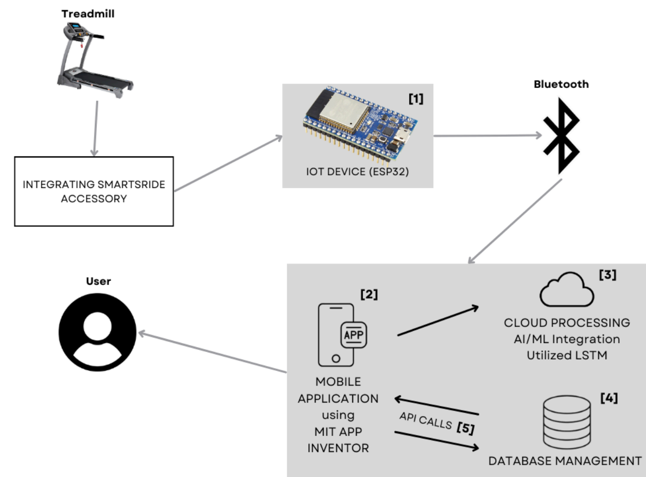

Figure 1: Architecture Diagram

2. Mobile App

The Mobile App serves as the primary interface for users to interact with the SmartStride system. It provides controls for starting, pausing, and stopping workouts, as well as displaying real-time data such as speed, distance, and calories burned. Additionally, the app facilitates communication with both the backend servers and the IoT device, allowing users to access personalised workout plans and track their progress over time.

3. Machine Learning

[7] SmartStride leverages machine learning, specifically LSTM (Long Short-Term Memory) models, to analyse the data collected from users during their workouts. These models process the data to understand patterns and trends in the user's exercise habits, allowing them to generate personalised workout plans tailored to individual fitness levels, preferences, and goals. This analysis is performed in the cloud, enabling continuous improvement and adaptation of the workout plans based on user feedback and performance metrics.

4. Database

The Database component of SmartStride stores a variety of user-related information, including user profiles, workout history, and system configurations. This data is stored securely in the cloud, ensuring accessibility from anywhere and facilitating seamless synchronisation across multiple devices. By centralising this information, SmartStride enables users to track their progress, review past workouts, and adjust settings as needed to optimise their fitness journey.

5. API Calls

FastAPI serves as the backbone for facilitating data exchange between different components of the SmartStride system. It enables seamless communication between the Mobile App, the cloud-based Database, and the Machine Learning models, allowing for efficient retrieval and processing of user data. This ensures a smooth and responsive user experience, enabling SmartStride to deliver personalised running patterns and insights in real time.

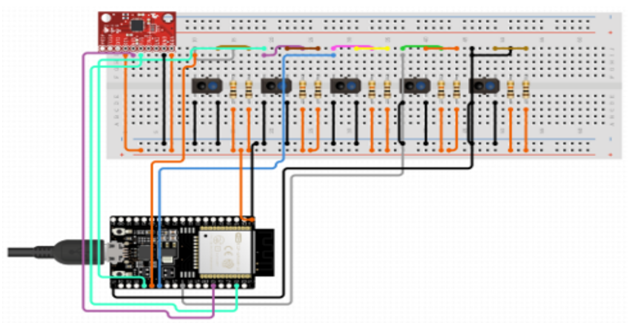

Figure 2: Circuit Diagram

As shown in **Figure 2** above, the IR Sensor (TCRT5000L) is a crucial component that tracks the speed of the treadmill by detecting a reflective marker placed on the belt. This sensor enables precise measurement of the treadmill's velocity, providing accurate data for analysis and feedback.

The Gyroscope Sensor (MPU-6050) plays a vital role in detecting the inclination of the treadmill. Measuring orientation changes, it helps determine whether the treadmill is flat or inclined, contributing to a more comprehensive understanding of the user's workout environment.
The ESP32 Bluetooth Module serves as the central processing unit for the IoT device. It collects data from the IR and gyroscope sensors, processes it, and transmits it wirelessly to the accompanying mobile app. This module enables seamless communication between the treadmill and the user's smartphone, facilitating real-time monitoring and analysis of workout metrics.

A reliable power source is essential to ensure the uninterrupted operation of the IoT device. Using a portable power supply, such as a lithium polymer battery, guarantees continuous functionality of the sensors and Bluetooth module, allowing users to engage in their workouts without any disruptions.

II. DATA FLOW

The data flow in SmartStride outlines the path data takes from collection at the IoT device through to storage and retrieval in the cloud database.

1. Data Collection at IoT Device (ESP32)

The ESP32 microcontroller, embedded in the accessory, collects various data points from sensors such as speed, distance, and inclination. These data points are processed and packaged into a structured format within the microcontroller's memory.

2. Data Transmission via Bluetooth Low Energy (BLE)

The ESP32 microcontroller communicates wirelessly with the Mobile App using Bluetooth Low Energy (BLE) technology. The packaged data is transmitted as Bluetooth packets every second. Contains relevant information about the user's workout session.

3. Data Reception and Processing in the Mobile App:

The Mobile App, installed on the user's smartphone or tablet, continuously listens for incoming Bluetooth packets from the treadmill's IoT device. Upon receiving data, the Mobile App parses and interprets the information, extracting metrics such as speed, distance, inclination and heart rate. It then updates the user interface to display real-time workout data, allowing the user to monitor their performance during the exercise session.

4. User Interaction and Feedback

The Mobile App also serves as the interface for user interaction, providing controls for starting, pausing, and stopping the workout session. Users can customise their workout settings and preferences through the Mobile App, such as setting target distances or adjusting incline levels. Additionally, the Mobile App may provide feedback to the user during the workout session, such as audio cues or visual notifications based on predefined thresholds or goals.

5. Data Storage and Retrieval in the SQL Database

The Mobile App communicates with a remote SQL database hosted in the cloud to store and retrieve user-related data. At the end of each workout session, the Mobile App uploads the collected workout data, including metrics and user settings, to the SQL database for storage. The SQL database stores user profiles, workout history, and system configurations, enabling users to track their progress over time and maintain personalised settings across multiple devices.

6. Data Exchange via Python FastAPI

FastAPI facilitates communication between the Mobile App, SQL database, and any other backend systems or services. It provides an efficient and secure mechanism for transferring data between the Mobile App and the SQL database, ensuring seamless integration and synchronisation of user data. FastAPI handles API calls initiated by the Mobile App to retrieve workout plans, update user profiles, or fetch historical workout data from the SQL database.

III. DATASET

The dataset component of SmartStride encompasses user profile data and previous run data to generate insightful graphs that guide workout plans.

1. User Profile Data

The initial segment of the dataset comprises user profile information, including age, height, and weight. This data serves as the foundation for generating the first graph, which delineates initial workout parameters tailored to individual users. By analysing these demographic variables, SmartStride formulates a baseline fitness plan optimised for the user's physical attributes and health goals.

2. User's Previous Run Data

After the establishment of the user profile, the dataset expands to incorporate data from the user's previous runs. These data points encompass various metrics such as distance covered, duration, average speed, calories burned, heart rate, and incline levels. Notably, the dataset prioritises recent runs, placing greater emphasis on the user's current capabilities and fitness level.

3. Graph Generation

Graphs are generated based on both the user's profile data and their previous run data. The initial graph, derived from user profile information, sets the groundwork for personalised workout plans as seen in **Figure 3.1**. Subsequent graphs, however, focus predominantly on recent run data. This emphasis on recent runs ensures that the generated graphs reflect the user's current fitness status and capabilities accurately.

4. Weightage Allocation

In the generation of subsequent graphs, particularly those about workout plans and performance analysis, more significant weightage is assigned to data from recent runs. By prioritising recent run performances, SmartStride ensures that workout plans evolve dynamically to align with the user's progressing fitness journey. This approach not only enhances the accuracy of the generated graphs but also facilitates the delivery of tailored workout experiences aimed at maximising user engagement and performance improvement. As a result, the graph generated on Day 1 **(Figure 3.1)** is very similar to the graph generated on Day 4 **(Figure 3.2)**, and likewise, the graph generated on Day 20 **(Figure 3.3)** is similar to the graph generated on Day 26 **(Figure 3.4)**, highlighting how recent runs are given more consideration.

IV. RESULTS AND ANALYSIS

The SmartStride system was applied to a dataset encompassing user profile data and information from previous runs. The following analysis presents key findings derived from this dataset.

1. User Profile Analysis

Analysis of the initial graph generated from user profile data revealed that SmartStride effectively utilises demographic variables such as age, height, and weight to tailor personalised workout plans. This suggests that the system can adapt workout recommendations based on individual characteristics.

2. Analysis of Previous Run Data

Examination of data from users' previous runs indicated various trends and patterns. Metrics including distance covered, duration, average speed, and incline levels were tracked. Notably, recent runs were given more weightage in the analysis to reflect users' current fitness levels accurately.

3. Impact of Recent Runs on Graph Generation

Prioritising recent run data in the generation of subsequent graphs ensured that workout plans accurately reflected users' evolving capabilities. By giving more weightage to recent runs, SmartStride effectively adapted workout recommendations to align with users' current fitness levels.

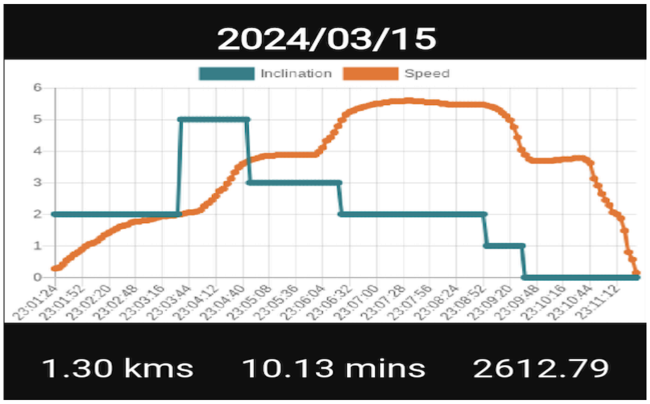

Figure 3.1: Graph generated by the model on Day 1

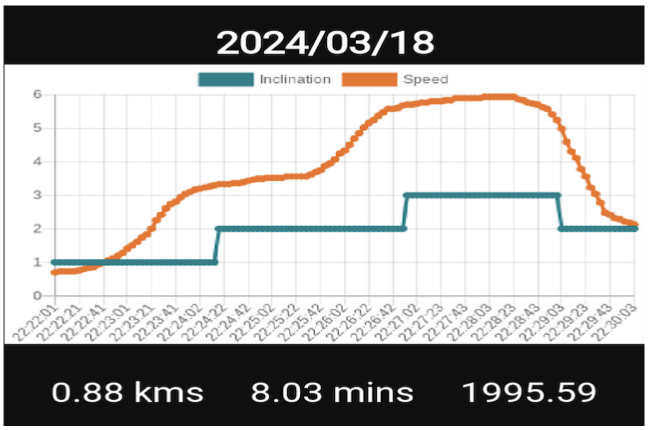

Figure 3.2: Graph generated by the model on Day 4

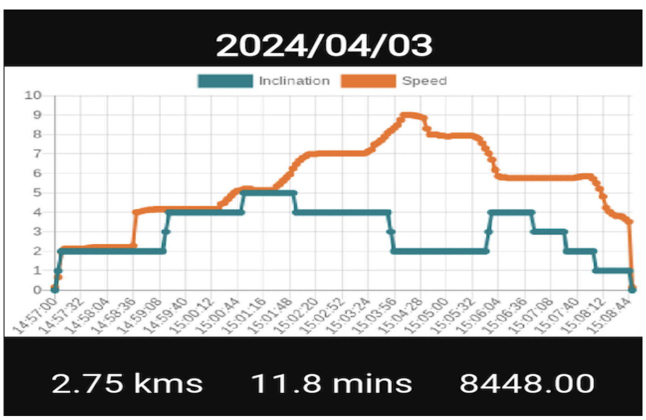

Figure 3.3: Graph generated by the model on Day 20

Therefore, the evaluation of SmartStride's personalised workout plans has demonstrated their efficacy in meeting users' fitness objectives, as evidenced by the increasing run volume over time shown in **Table 1**. The adaptive nature of these recommendations has contributed to sustained user engagement and satisfaction. These findings underscore the potential of SmartStride to revolutionise the fitness industry by providing tailored solutions that align with individual needs and preferences.

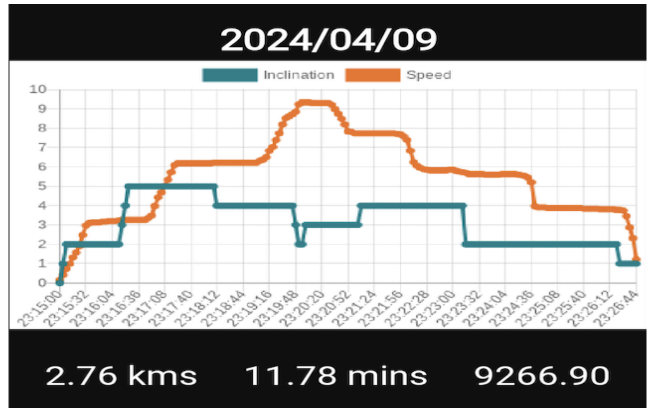

Figure 3.4: Graph generated by the model on Day 26

Table 1: Run data

Date	Distance	Time	Run Volume
2024/03/15	1.30 km	10.13 mins	2612.79
2024/03/18	0.88 km	8.03 mins	1995.59
2024/04/03	2.75 km	11.8 mins	8448.00
2024/04/09	2.76 km	11.78 mins	9266.90

Incorporating the IR Sensor, Gyroscope Sensor, Bluetooth Module, and power source into a custom 3D printed case (**Figure 4**) made from PLA (Polylactic Acid) ensures a compact and robust solution for SmartStride. This housing not only protects the delicate electronic components but also allows for easy attachment to the treadmill's side. By integrating these elements into a unified enclosure, SmartStride achieves a sleek and ergonomic design while maintaining functionality and durability, providing users with a seamless and hassle-free fitness experience.

4. Hardware results

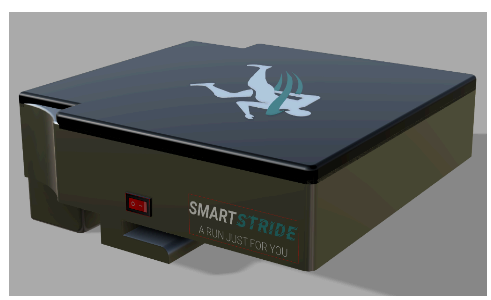

Figure 4: Design Prototype of the IoT Device

V. LIMITATIONS

While SmartStride presents a significant leap forward in personalised fitness technology, there are limitations in the current prototype that future iterations aim to address. The current system relies on infrared (IR) sensors to track user movement, requiring a white marker on the treadmill belt, which can be inconvenient and visually distracting for some users. Future iterations will explore alternative sensor technologies, such as embedded pressure sensors or camera-based tracking systems, to eliminate this requirement and enhance user experience. Additionally, the mobile app controlling SmartStride and displaying workout data is currently only compatible with Android devices, limiting accessibility. Expanding compatibility to iOS devices is crucial to ensure.

VI. FUTURE WORK AND CONCLUSION

SmartStride ushers in a new era of personalised fitness technology, transforming the traditional treadmill into an intelligent companion. By harnessing the power of machine learning and seamless IoT integration, SmartStride empowers users to achieve their fitness goals more effectively and enjoyably. The ability to generate personalised workout plans, track real-time data, and receive tailored coaching fosters a more engaging and motivating exercise experience.

As we look to the future, SmartStride's journey is far from over. One key area of focus is refining the machine learning model to provide even more sophisticated and data-driven workout recommendations. Furthermore, compatibility with popular fitness trackers like Fitbit and Apple Watch will unlock a treasure trove of user health data, enabling SmartStride to create personalised workout plans that consider overall well-being. By relentlessly pursuing these advancements, SmartStride aspires to become the gold standard for smart treadmills, offering users a personalised journey towards peak performance.

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