SmartDampener: An Open Source Platform for Sport Analytics in Tennis

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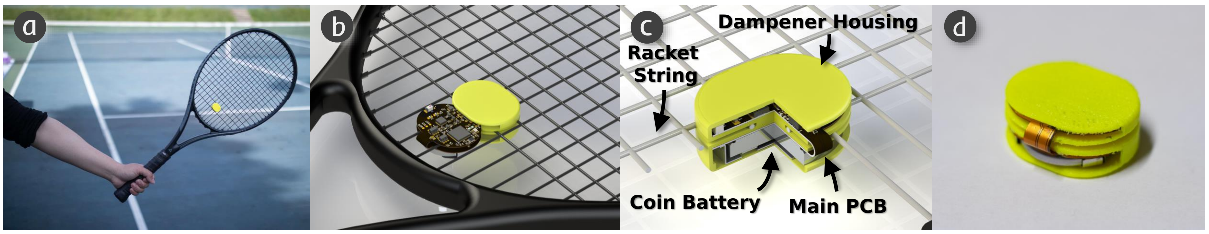

Fig. 1. *SmartDampener* is designed by integrating motion sensor and wireless connectivity into the form factor of a commonly used vibration dampener, enabling the analytics of diverse tennis stroke matrices. (a) Real-world mounting and using of *SmartDampener* (b) 3D rendered mounting indication of *SmartDampener* on racket (c) Cross-section view of *SmartDampener*. Mechanically, the circuitry of *SmartDampener* is implemented on a flexible PCB and housed within a 3D-printed enclosure made of TPU material, allowing effortless installation and preserving dampening properties on par with conventional dampeners. (d) Final prototype of *SmartDampener* excels in retaining a size and weight similar to a traditional dampener while achieving battery life that far exceeds a full tennis match session.

In this paper, we introduce *SmartDampener*, an open-source tennis analytics platform that redefines the traditional understanding of vibration dampeners. Traditional vibration dampeners favored by both amateur and professional tennis players are utilized primarily to diminish vibration transmission and enhance racket stability. However, our platform uniquely merges wireless sensing technologies into a device that resembles a conventional vibration dampener, thereby offering a range of tennis performance metrics including ball speed, impact location, and stroke type. The design of *SmartDampener* adheres to the familiar form of this accessory, ensuring that (i) it is readily accepted by users and robust under real-play conditions such as ball-hitting, (ii) it has minimal impact on player

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performance, (iii) it is capable of providing a wide range of analytical insights, and (iv) it is extensible to other sports. Existing computer vision systems for tennis sensing such as Hawk-eye and PlaySight, rely on hardware that costs millions of US dollars to deploy with complex setup procedures and is susceptible to lighting environment. Wearable devices and other tennis sensing accessories, such as Zepp Tennis sensor and TennisEye, using intrusive mounting locations, hinder user experience and impede player performance. In contrast, *SmartDampener*, a low-cost and compact tennis sensing device, notable for its socially accepted, lightweight and scalable design, seamlessly melds into the form of a vibration dampener. *SmartDampener* exploits opportunities in SoC and form factor design of conventional dampeners to integrate the sensing units and micro-controllers on a two-layer flexible PCB, that is bent and enclosed inside a dampener case made of 3D printing TPU material, while maintaining the vibration dampening feature and further being enhanced by its extended battery life and the inclusion of wireless communication features. The overall cost is \$9.42, with a dimension of 21.4 mm × 27.5 mm × 9.7 mm (W × L × H) and a weight of 6.1 g and 5.8 hours of battery life. In proof of *SmartDampener*'s performance in tennis analytics, we present various tennis analytic applications that exploit the capability of *SmartDampener* in capturing the correlations across string vibration, and racket motion, including the estimation of ball speed with a median error of 3.59 mph, estimation of ball impact location with accuracy of 3.03 cm, and classification of six tennis strokes with accuracy of 96.75%. Finally, extensive usability studies with 15 tennis players indicate high levels of social acceptance of form factor design for the *SmartDampener* dampener in comparison with alternative form factors, as well as its capability of sensing and analyzing tennis stroke in an accurate and robust manner. We believe this platform will enable exciting applications in other sports like badminton, fitness tracking, and injury prevention.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**.

Additional Key Words and Phrases: IoT, Wearable Computing, Sport Analytics, Wireless Sensing

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1 INTRODUCTION

A large industry is growing around sports analytics where the main goal is to sense, infer, and analyze various sports activities, such as strokes, player gestures, racquet movements, strategies, etc. [30, 45, 50, 55]. iBall [43] proposes a wireless sensor fusion system by utilizing an inertial measurement unit (IMU) and motion models to track a cricket ball's 3D trajectory and spin by embedding radio sensor inside the ball. Moreover, multiple popular commercial products such as Zepp [25], Babolat POP [13], Head [17], Qlipp [20], Sony Smart Tennis [21], and Courtmatics [14] can track ball's motion and players' behavior. Consequently, the sports market of global commercial wearable devices is booming and expected to reach \$106.47 billion in 2028 with expecting to have a compound annual growth rate (CAGR) of 4.18% in the next few years [24].

In various racket sports, including tennis, badminton, and table tennis, comprehending the racket's stroke dynamics, particularly its interaction with the ball, is vital for analyzing and enhancing player performance [18]. For example, ball speed, ball spin, impact location, and stroke types are crucial metrics for stroke evaluation in racket sports. Ball speed and spin allow the player to evaluate the strength and effectiveness of their strokes, while ball impact location provides feedback on the precision of a player's shots. Furthermore, analysis of tennis stroke types enables players and coaches to work on diversifying their shot selection. Analytical data on players' performance can pinpoint their specific areas of deficiency, enabling targeted improvements and expedited progress.

Toward this end, this paper designs a smart dampener platform called *SmartDampener* with the following goals: (i) Form factor embraced by the tennis community and characterized by its lightweight and compact dimensions. (ii) Wireless communication with mobile device streaming data for sports analysis (iii) Long battery life (iv) Capability to cover a wide range of ball's characteristics and player's motion (v) Low cost (vi) Scalability to add additional sensors or actuators (vii) Reliable mechanical design to sustain under ball-hitting condition.

With prior vision processing techniques, using cameras such as PlaySight [19], SwingVision [23] and Hawk-eye technology [16] can capture ball movement and player's activity [39]. However, cameras can be susceptible to interference from occlusions and lighting conditions and are very expensive and complex to set up. Therefore, most players do not have access to these systems. In addition, these systems lack the capability to capture finer grain information, such as impact location, as the human body tends to obstruct the camera view during tennis play. In contrast to cameras-based systems, motion sensors-based systems are more affordable, power efficient, easy to set up, and prone to bad lighting conditions, while being capable of capturing multi-dimensional information including ball speed, impact location, and stroke type. Lots of recent works in the field of ubiquitous computing focus on accessing player performance [48, 73, 74]. However, these systems disrupt players' natural grip and playing style due to bulky form factors caused by sub-optimal PCB design. In addition, they encounter resistance within the tennis community as an unusual tennis accessory while suffering from a dearth of stroke information due to the long distance between sensor placement and hitting area. On the other hand, there are some commercial products such as [14, 17, 20, 21, 25] available on the market to evaluate the performance of players. However, these systems are closed without any details about the software or hardware and there are no APIs available to access the raw sensor data. In contrast to such works, we design an open-source smart dampener platform that integrates the capability of evaluating ball speed, impact location, and stroke types altogether while sharing full details of hardware, software, and firmware. We will open-source our platform with this paper for the community to further develop interesting applications.

Designing a smart dampener is challenging for a number of reasons: (i) The use of large electronic devices is categorically impractical due to their potential interference with player movements (ii) At professional or semi-professional levels, any physical change to the racket is almost unacceptable, thus necessitating any electronic sensors modality to be integrated into existing racket components or accessories. (iii) The device system must possess mechanical compatibility to allow for effortless integration into existing rackets and mechanical reliability to sustain high intensity of player activity. (iv) There is no state-of-the-art data collection method for collecting impact location, stroke types, and speed simultaneously. (v) The interaction between a tennis ball and tennis racket is characterized by a highly transient and complex dynamic process, which results in noisy or under-sampled sensor data. (vi) Players with different proficiency levels and dominant hands have diverse swing characteristics. Players may also use either side of the racket to counterattack an incoming ball. *SmartDampener* must provide consistent accuracy across diverse variations.

Towards solving the above challenges, Fig. 2 depicts the overview of *SmartDampener*. *SmartDampener* exploits a number of opportunities in hardware and multi-stage optimized algorithms: (i) We exploit to design a custom micro-controller and sensing based on system-on-chip (SoC) architecture, to decrease the form factor size while satisfying the requirements of embedded sensing and electronics. (ii) Considering that most tennis players attach vibration dampeners to their racket to reduce the vibration of racket strings, we exploit flexible printed circuit (FPCB) technology that can bend PCB within the form

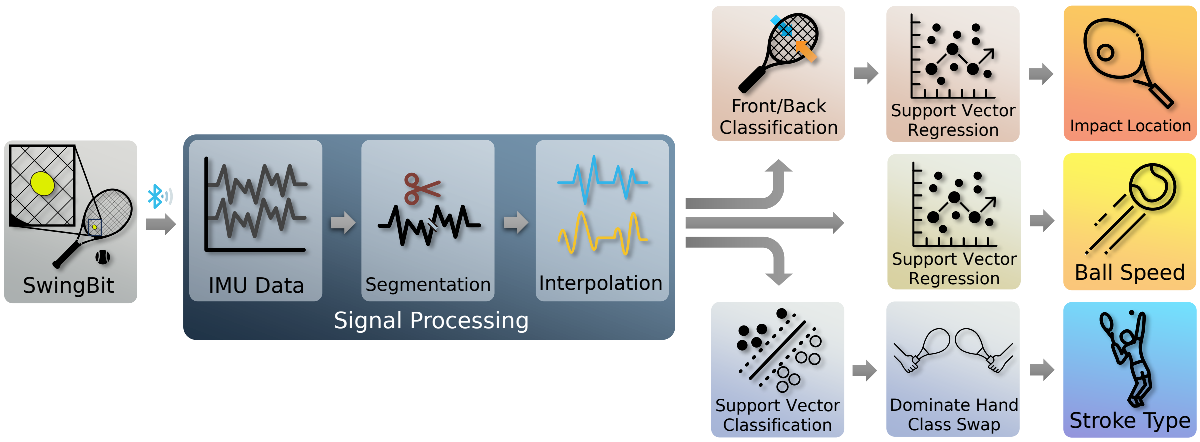


Fig. 2. System Overview

factor of a widely adopted dampener, as shown in Fig. 1. The deliberate selection of this specific form factor allows professional or semi-professional players to seamlessly incorporate *SmartDampener*, without encountering any adverse effects on their game performance. (iii) We exploit the form factor design of existing conventional vibration dampeners and 3D-printed technology to custom an easy-to-use smart dampener. Its housing is made of Thermoplastic Polyurethane (TPU) material to provide comparable dampening properties to a conventional dampener made of rubber or silicone. (iv) Leveraging on the data collection method of badminton's impact point [52], we collect a dataset to implement and evaluate *SmartDampener*. (v) With signal processing and machine learning techniques applied, we have multi-stage algorithms to separate out and process each stroke event, then perform analysis on them accurately. (vi) We conducted an extensive user study encompassing diverse proficiency levels, genders, and playing habits to validate the robustness and precision of our system.

An extensive user experience study is also conducted, in which *SmartDampener* satisfies the users with high ratings across multiple dimensions such as acceptance, weight, and ease of use, demonstrating the high acceptability of such dampener-based form factors in the community. For validating sports analysis performance, a systematic study with diverse users achieves an accuracy of 3.59mph for ball speed estimation, a precision of 3.03cm for estimation of ball impact location, and an accuracy of 96.75% for stroke classification of 6. Furthermore, the performance is consistent over various players, sensor placement, and longer duration of the real-playing experiment. In the realm of tennis stroke analytics, *SmartDampener* exhibits high precision and maintains solid robustness across a diverse range of users, player skill levels, and other variables. More details are elaborated in Sec. 6.

We enumerate our contributions below: ■ To our best knowledge, the first design of a sensor-embedded smart dampener by exploiting opportunities in a form factor design of existing real vibration dampener, 3D printing material, flexible PCB, and low-cost manufacturing to reliably allow continuous ball motion and player's activity tracking for a long time while ensuring widely acceptance within tennis community. ■ Demonstrated feasibility, precision, and stability of analyzing tennis strokes, ball speed, and ball impact location for sports analysis with *SmartDampener* in the shape of dampener and design of signal processing and analytic models, that identifies opportunities in correlations between racket motion, stroke characteristics, and player activity. ■ Conducted a systematic user study across varied users to validate the community acceptance and comfort levels of *SmartDampener* as well as the performance of ball motion and player activity tracking with robustness to user diversity, changes in sensor placement, and ability to perform under real-play conditions. ■ We will open-source *SmartDampener* for the community to explore it with novel capabilities in hardware and use cases. Although we present the paper in the context of tennis, the core ideas and the platform can be generalized to other sports analytics use-cases as well.

2 RELATED WORK

In this section, we review previous work on assisting tennis with wearables, computer vision, and machine learning, as well as other sports analytics applications.

Table 1. Summary of Main Related Work

System	Sensor Placement	Dimension	Weight (g)	Stroke Types	Speed	Impact Location	Open-source
Anand et al [28]	Wrist	49.8 mm × 42.3 mm × 11.4 mm (W × L × H)	54	5	✗	✗	✗
Mlakar et al [53]	Player's back	N/A	N/A	3	✗	✗	✗
Büthe et al [36]	Handle & Foot	54 mm × 33 mm × 14 mm (W × L × H)	22	5	✗	✗	✗
Pei et al [60]	Handle	N/A	N/A	6	✗	✗	✗
TennisMaster [73]	Handle & Wrist	47 mm × 43 mm × 17 mm (W × L × H)	N/A	1	✗	✗	✗
TennisEye [74]	Handle	50 mm × 30 mm × 11.7 mm (W × L × H)	N/A	3	✓	✗	✗
Qlipp [20]	Dampener	30.3 mm × 26.7 mm × 10.7 mm (W × L × H)	8	6	✓	✗	✗
Zepp [25]	Handle	25.4 mm × 25.4 mm × 12.3 mm (W × L × H)	20.4	5	✓	✓	✗
Head [17]	Handle	N/A	7	5	✓	✓	✗
Courtmatics [14]	Dampener	20.32 mm × 20.32 mm × 12.95 mm (Dia × W ×H)	6.24	4	✓	✗	✗
Sony Smart Tennis [21]	Handle	31.3 mm × 17.6 mm (Dia ×H)	8	6	✓	✓	✗
***SmartDampener* (Ours)**	**Dampener**	**21.4 mm × 27.5 mm × 9.7 mm (W × L × H)**	**6.1**	**6**	✓	✓	✓

2.1 Wearables

Table 1 summarizes a comparison between *SmartDampener* and prior works in the field of wearable computing. Several sensors-based systems mount motion sensors on the wrist for tennis stroke detection and classification [28, 35, 48]. Furthermore, some researchers exploit the interaction between the racket and the ball by mounting the sensor on the handle [53, 60, 74]. TennisEye [74] introduces an approach of placing an IMU sensor above the handle for stroke classification and tennis ball speed estimation. [60] proposes to mount an IMU sensor on the handle to detect 6 tennis strokes. Nevertheless, their positionings of the sensors limit their sensing range in these systems because their placement on the wrist or handle is significantly distant from the area of impact. While prior works adopt certain electronic components for rapid prototype development, this results in a bulky form factor because such components can be suboptimal for overall device size when integrated together. *SmartDampener* embeds a motion sensor inside a smart dampener mounted on racket string, as depicted in Fig. 1, to exploit insight into the shots for stroke types, speed, and impact point. Moreover, the fusion of electronic components within a tennis dampener, a widely utilized accessory in tennis, enables the tracking of ball motion and player activity, meanwhile serving the dual function of mitigating string vibrations, akin to conventional dampeners. Among commercially available tennis sensors [14, 17, 20, 25], Qlipp [20] and Courtmatics [14] are perhaps the closest to our platform. Nevertheless, the technical details are closed-source due to the proprietary nature of the hardware and there is no access to the raw sensor data for developers. To our best knowledge, *SmartDampener* is the first open-source dampener-form factor sensors that fulfill all of the design requirements discussed in the third paragraph of Sec. 1.

2.2 Computer Vision

In computer vision technology, single camera-based methods [61, 72] propose to track tennis ball trajectories from low-quality single-camera videos. [72] proposes a tennis ball tracking algorithm from a single camera by exploiting advances in modified particle filters. [37] introduces a system for 3D table tennis ball trajectory analysis using a single camera. Tracknet [44] and [62] track the position of a tennis ball from broadcast videos. However, only partial and limited ball position data can be extracted from single-camera videos or broadcast videos. To collect more data, recent researchers use multiple dimensional video data to analyze tennis ball motion [38, 67, 68, 74]. There have been several commercial products for multiple dimensional tennis ball tracking, such as SwingVision [23], Hawk-eye technology [16, 57], PlaySight [19] and AccuTennis [12]. However, the majority of tennis courts lack these systems as cameras are considered invasive to privacy and require optimal lighting, high resolution, intricate installation, and significant financial investment in hardware that often amounts to tens of thousands of dollars. In contrast, *SmartDampener*'s solution is ubiquitous and low-cost while being robust to ambient conditions.

2.3 Algorithms for Sport Analytics

A variety of algorithms has been applied for tennis analytics including Hidden Markov Model [73], regression model [63, 74], SVM [70], Convolutional Neural Network (CNN) [62], Deep Learning Models [44, 54]. TennisEye proposes two models including a physical model and a regression model to estimate ball speed [74]. TennisMaster applies Hidden Markov Model to segment a tennis serve into 8 phases [73]. Recently, MonoTrack proposes a Recurrent neural network (RNN) for shot segmentation and 3D shot trajectory estimation for badminton without human intervention. Conversely, *SmartDampener* integrates a differential shot segmentation technique, a machine learning algorithm for identifying the racket side, and three distinct support vector models dedicated to the final objective of tennis analytics. *SmartDampener* incorporates the design of various machine learning based algorithms and data processing techniques, forming a processing pipeline to achieve multiple tennis analytic tasks.

3 THE SMARTDAMPENER PLATFORM

In this section, we describe the platform design of *SmartDampener* for sports analytics in tennis. First, we elaborate on the design principles of *SmartDampener*. Later, we discuss the form factor, hardware, and software.

3.1 Design Principles

Our main goal of developing *SmartDampener* is to design a general-purpose hardware sensing platform for the wearable research community that allows for the discovery of sensing capabilities on dampener form factor devices. We were guided by the following principles when designing *SmartDampener*.

Aesthetics and Community Acceptance: *SmartDampener* must ensure an elegant appearance and pleasing aesthetics as a real tennis dampener, maintaining an appearance that the tennis community is familiar with and widely accepts. Existing commercial platforms such as Sony Smart Tennis, Zepp, Qlipp, Courtmatics, and Head [14, 17, 20, 21, 25] have attracted a lot of attention recently [22]. Giménez-Egido et al conducted an extensive study and validated that Zepp Tennis 2 improves the performance of players in tennis at low cost[42] These studies demonstrate that the integration of sensors within pre-existing tennis accessories familiar to tennis players offers significant utility and garners community acceptance.

Therefore, we envision that *SmartDampener* is readily and rapidly acceptable to a broad range of players.

Longer Battery Lifetime and Easy Charging: Energy constraints come along with inevitable form factor constraints since a tennis game may last for several hours; continuous sensing must be feasible during the entire session with a tiny battery. *SmartDampener* is designed with a low-power microcontroller and a rechargeable battery for a long time. This allows players to continuously use *SmartDampener* without the hassle of frequent battery charging.

Wireless Communication: The *SmartDampener* platform is designed to wirelessly communicate with mobile devices, providing convenience of connection during gameplay for users. This wireless communication with minimal disruption maintains the common appearance of a real tennis dampener. *SmartDampener* is composed of an SoC integrated with BLE radio while maintaining low-power consumption and miniature form factor.

Coverage of a Wide Range of Applications: *SmartDampener* has various applications that provide valuable insights into user performance. For example, *SmartDampener* can capture data on shot quality such as tennis strokes, ball speed, and ball impact location. While *SmartDampener* provides insightful information to users for shot analysis to improve performance, it should offer other applications like training aid, match analysis, and social interaction.

Openness and Extensibility: The research community should be able to easily extend *SmartDampener*'s hardware and software platform. Given the small size of *SmartDampener*, *SmartDampener* only integrates IMU sensor in the current version, which can still cover a wide range of sports analytics. However, other sensors such as microphone, pressure, and force sensors can be integrated depending on the design need of a use case. We believe open-sourcing *SmartDampener* will promote extensibility.

Reliability and Compatibility of Mechanical Design: The performance of *SmartDampener* is designed to be robust in real play conditions, while maintaining in minimal interruption to the player. Because it is unavoidable that the ball will hit the sensor device of *SmartDampener* in the context of a real-world scenario, the mechanical design of *SmartDampener* should be reliable in real play conditions such as ball-hitting conditions. In addition, *SmartDampener* is designed to have user-friendly functionality and broad compatibility in daily life. Players can seamlessly integrate *SmartDampener* into using their existing racket without the need for any additional adjustments or equipment. This feature allows players to continue using their preferred racket effortlessly. They can easily mount or dismount *SmartDampener* as commonly used tennis dampeners, enhancing the overall ease of use. It is particularly important to maintain compatibility with different racket models and string setups when designing *SmartDampener*. This compatibility ensures that a wide range of players can readily adopt *SmartDampener* without requiring significant changes to their existing equipment.

Manufacturability and Cost-Effectiveness: To leverage the *SmartDampener* platform for the research and sports community, the platform must be easily manufactured at an affordable cost. To achieve this, the platform is designed with a composition of low-cost commercial off-the-shelf (COTS) electronic components and housing cases fabricated of 3D printing material.

3.2 Platform Design

Form Factor Design: Our goal is to design a lightweight, community-accepted, and unobtrusive smart dampener that can work as a real tennis dampener while being embedded with electronics and sensors that can sense ball motion and player activity and stream the data wirelessly for sports analytics. Therefore, we exploit the following opportunities to maintain the form factor of a tennis dampener with embedded sensing and electronics while satisfying the functionality of commonly used dampeners. (i) We design the electronics using an FPCB that we bend as illustrated in Fig. 3. We assemble a custom microcontroller and sensing hardware into the FPCB, and the details will be elaborated on shortly. We also integrate a replaceable and rechargeable LIR2032 coin cell battery (Fig. 3) to power the hardware. (ii) We enclose the hardware inside the shape of a dampener, whose material is designed to fit on the string of tennis rackets.

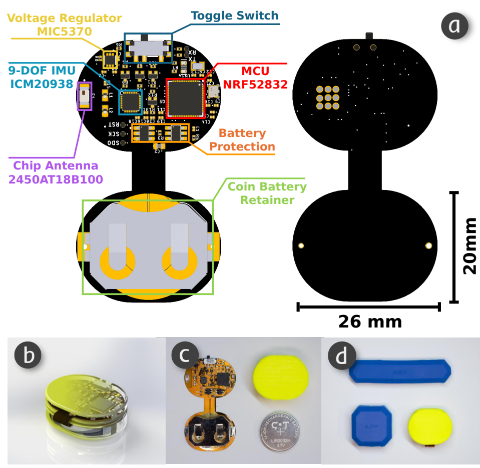


Fig. 3. **(a)** Layout and component of FPCB. **(b)** 3D Rendering. **(c)** Components of *SmartDampener*. **(d)** Comparison of *SmartDampener* and tennis vibration dampener.

Hardware and Power Circuitry: We started with a schematic design of micro-controller module to minimize form factor size while combining sensing devices and electronics. We have integrated features including (i) Sensing hardware which includes IMU sensor in the current revision of *SmartDampener* (ii) A microcontroller (MCU) to collect data from the IMU and stream wirelessly to a smartphone companion app. (iii) A BLE module for communication with a smartphone companion app. (iv) Battery circuitry to support diverse requirements of the above hardware components. Various hardware components were carefully assembled into a double-sided FPCB as shown in Fig. 3 to fit the form factor requirements. We redesigned NRF52832 [10] MCU which interfaces with the rest of the electronics based on the design of [75], as shown in the layout diagram Fig. 3a. The MCU consists of a 2.4 GHz radio frequency (RF) transceiver for BLE and ARM Cortex-M4 32-bit 64 MHz processor with floating-point unit (FPU) and supports multiple interfaces such as SPI, I2C, and UART. The IMU chip incorporated is ICM20948 [2] which provides 9-axis IMU data and interfaces with the MCU using the SPI protocol. The whole PCB is powered with a 70 mAh, 3.7V rechargeable lithium-ion coin battery, supplying 5.8 hours of data streaming. Overall, the power consumption of the hardware is about 12 mA when actively streaming the sensor data to the smartphone app.

Mechanical Design: Fig. 1 depicts the mechanical design of *SmartDampener*. To fulfill mechanical design requirements as discussed in Sec. 3.1, we exploit the opportunity of mechanical design and material of existing vibration dampeners. We design *SmartDampener* as depicted in Fig. 1c. Players can easily affix and disengage *SmartDampener* as a real dampener. *SmartDampener*'s dampener housing is manufactured using fused deposition modeling (FDM) technology with TPU materials. While TPU allows *SmartDampener* to sense string vibration and reduce the amount of vibration as a real dampener, *SmartDampener* can be tightly mounted above string, as depicted in Fig. 1c. The dimension of *SmartDampener* is 21.4 mm × 27.5 mm × 9.7 mm (W × L × H), which is much smaller than existing commercial products like Qlipp [20] and Courtmatics [14]. It weights 6.1g and is comparable to the commercially available dampener which weighs 5g [7].

Fig. 4. Demo Application

Software Framework: The *SmartDampener* phone Application is developed for iOS and Android using the React Native framework, which can be used for developing cross-platform mobile applications for iOS and Android platforms. The *SmartDampener* communicates with the APP via BLE using a custom GATT profile with a sampling rate of 100 Hz. Fig. 4 depicts *SmartDampener* real-time demo on a smartphone device implemented with the ML modules for stroke classification, ball speed, and ball impact location. More details on data processing are discussed in Sec. 6.2.

Price Breakdown: The retail and wholesale unit price for each major hardware component is summarized in Table 2. All firmware packages and programs developed for *SmartDampener* are made at no cost. The total cost to produce a single *SmartDampener* platform is as low as $9.42, much lower than the price of existing commercialized smart dampeners like Qlipp [20] and Courtmatics [14].

Table 2. Manufacturing Cost Breakdown

Electronic Component	Unit Price (Retail) [U$]	Unit Price (Wholesale) [U$]
MCU (NRF52832)	5.02	2.23
IMU Sensor (ICM20948)	26.45	5.62
Chip Antenna	0.59	0.23
Voltage Regulator ICs	1.47	0.80
Battery Protection ICs	0.32	0.18
Case	0.01	0.01
Battery	1.57	0.35
Total	35.43	9.42

Firmware and Phone Application: The firmware of *SmartDampener* includes two main components: (i) Collecting the data from the IMU sensors at the microcontroller; (ii) Streaming data over BLE connection to a smartphone. We use C++, Arduino, and BLE libraries for implementing the functionalities [26, 27]. The *SmartDampener* companion application allows interaction with the platform. The firmware and the phone app use popularly available Arduino and Android frameworks, thus *SmartDampener* can be easily extensible by developers to incorporate additional features.

4 USE CASE ANALYSIS

In this section, we will provide a brief overview of potential use cases of *SmartDampener*.

Smart Sport Training: With the increasing involvement of people in sports activities like tennis, the need for coaching and training in sports activities is increased [56]. Many players struggle to hire a professional sports trainer because of various challenges, including financial constraints. The use of wearable technology in daily sports activities is popular nowadays as it offers an affordable and convenient solution for players to improve their training performance in sports events [47]. We believe that *SmartDampener* can help players improve training performance at an affordable cost while providing valuable information to users such as shot analysis, ball speed, sweet spot precision, stroke statistics, and impact point detection.

Mixed Reality in Sports:
In the AR/VR environment, even though there is no physical impact, haptic feedback can potentially be integrated into the smart dampener to provide a feeling of hitting a real ball to the user who is in an AR/VR environment. The sensing data collected from real plays using *SmartDampener* can inform the actuators in the haptic system to provide similar feels for the user in an AR/VR environment. The raw IMU data from the smart dampener can still be used for stroke analysis in AR/VR environment. In general, the application of virtual reality (VR) technology to sports has attracted intense interest recently. For example, VR can play the role of virtual trainer when playing racket sports for exercise and training [51]. A combination of an Unity game engine and digital glove enhances players' physical feedback in the application of baseball training software [64] in VR or AR environment. To enable the integration of VR into *SmartDampener*, *SmartDampener* can integrate haptic feedback mechanisms, such as vibration motor [8] and piezoelectric actuators [6], which can be seamlessly integrated into *SmartDampener*'s sensor device to generate haptic feedback to users. For example, to emulate the sensation of a tennis ball striking a racket, a vibration motor could be strategically embedded within the sensor device of *SmartDampener* to simulate the tactile feedback associated with such impact, even though the impact between the ball and the racket did not physically occur. With the combination of haptic technology and *SmartDampener*, users can engage in peer-to-peer tennis matches that closely replicate the sensory experience of real-life gameplay. We also envision that *SmartDampener* can recognize the motion of users as an input device such as a smart glove, as depicted in Fig. 5a, for a number of VR applications such as education [41] and training [51].
Injury Prevention: Users often experience in heavy vibrations and shocks during play, which potentially cause discomfort or injury. *SmartDampener* can capture vibrations at impact, warning the user of possible discomfort. *SmartDampener* can exploit IMU data to detect player motions that may potentially result in injury, providing corrective suggestions. In our vision, *SmartDampener* could be incorporated into a

Fig. 5. **(a)** Use case of *SmartDampener* in smart glove. **(b)** Use case of *SmartDampener* in sport headband. **(c)** Use case of *SmartDampener* in badminton.

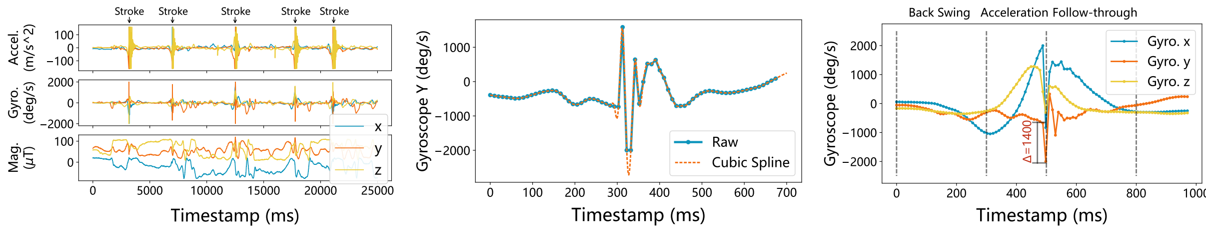
headband, enabling it to monitor potentially hazardous movements while the wearer participates in various sports activities. This integration aims to alert users to potential injury risks during sports engagement.

Extensibility to other Sports: With careful consideration during the design process, *SmartDampener* has a lightweight and a miniature form factor, as discussed in Sec. 3, that is capable of being adapted to other sports such as badminton, golf and table tennis, as depicted in Fig. 5c. *SmartDampener* can be easily mounted on instruments related to a variety of sports due to its adaptable design. Additionally, *SmartDampener* can be attached inside smart clothes to monitor player performance. we envision *SmartDampener* supports diverse applications in sports.

Sports Activity Visualization: *SmartDampener* can provide users with intuitive and comprehensive insights into their performance via visualization techniques, allowing them to easily interpret and analyze their playing patterns. As users play, *SmartDampener* collects data on various aspects of their performance, such as shot speed, spin rate, and impact location. After the session, the player accesses the companion mobile app, which presents visualizations of users' performance data. For example, the mobile app can show a heat map of the ball's impact location on the racket, with the ball speed and stroke type, as shown in Fig. 4. By interpreting this visualization, users can identify patterns in their shot placement, such as favoring one side of the tennis racket or consistently hitting shots with high speed. With this insight, users can adjust their strategy and focus on areas of their game that may need to improve.

5 TENNIS STROKE ANALYTICS WITH SMARTDAMPENER

Among the several potential use cases of *SmartDampener* mentioned in Sec. 4, we validated its capability of analyzing tennis player performance by presenting the feasibility and robustness analysis of detecting multiple characteristics of tennis shots utilizing the IMU sensor integrated into *SmartDampener*. These characteristics include stroke type, ball speed, and impact location. In this section, we will present multiple



(a) **(b)** **(c)**

Fig. 6. (a) Clip of IMU Data During Tennis Rally (b) Example of Cubic Spline Interpolation (c) Example of IMU Data of One Stroke

stages of data processing and various machine learning models that we designed to approach the problem. A glance at the processing system is shown in Fig. 2.

5.1 IMU Data Pre-processing

5.1.1 The IMU Data: As we mentioned in Sec. 3, *SmartDampener* is designed to be mounted on the racket at a location where tennis players usually place their vibration dampener. Thus the IMU sensor in *SmartDampener* will precept both the player's movement and the ball's impact on the racket. An IMU is composed of an accelerometer, a gyroscope, and a magnetometer. The accelerometer measures the combined effect of acceleration and gravity vector. The magnetometer measures the direction of the magnetic field. The gyroscope measures angular velocity. The accelerometer, magnetometer, and gyroscope sensors can be used to determine an object's movement, orientation, or changes of position.

5.1.2 Stroke Segmentation: Fig. 6a showed a clip of IMU readings during a period of a tennis rally. We observed spikes that correspond to strokes and lower amplitude components that represent the player's movement. For further stroke analysis, it is necessary to segment the IMU time series into individual strokes as all the events happen in quick succession. Using the segmented stroke IMU data, we can estimate stroke type, ball speed, and impact location. We use the gyroscope data for segmentation because its variation is stronger based on empirical observations. In previous works, such as TennisEye [74], IMU readings are segmented by setting an absolute magnitude threshold to capture the spikes, i.e. the strokes timestamps are determined by whether at time t the gyroscope y's magnitude Gy_t exceeded the defined threshold respect to 0. However, the occurrence of an impact is always after a fast back-swing. In this case, the impact spike may originate from non-zero magnitude and the actual absolute spike magnitude is higher. Fig. 6c shows one such case. The above method may be unable to capture strokes or segment strokes with shifted offsets in similar cases. We introduce the temporal magnitude difference method, which uses a sliding window of 2-timestamp wide to compare the magnitude at the current timestamp G_t with the magnitude at the previous timestamp G_{t-1}. We can determine a timestamp as the occurrence of a stoke, if on any gyroscope axis, the absolute value of $G_t - G_{t-1}$ is higher than a threshold we defined. The moving window is applied on the $x/y/z$ axis of the gyroscope to ensure impacts from all possible directions are considered. We found empirically that 400degree/s is the best fit for this threshold to capture all spikes in our samples. Afterward, a 2000ms slice of IMU data will be preserved for each stroke, centered to the impact occurrence timestamp. We selected such a window size since there are multiple stages in a complete player motion for a stroke, including back swing, acceleration, impact, and follow-through, as shown in Fig. 6c. In most of our samples, back swing and acceleration together take at most 1000ms, and follow-through can finish within 1000ms in most cases. The accuracy of successful segmentation using the above method is shown in Sec. 6.3.

5.1.3 Resampling and Interpolation: Even though the miniature IMU sensor has a wide sensing range, we still observed sensor saturation in instances of intense ball impact on the racket. Fig. 6b showed a snippet of raw gyroscope y data with saturation occurred. We assume that such saturation may affect the model fitting of speed estimation and impact location detection. Meanwhile, to maximize the sampling and transmission rate, we designed the *SmartDampener* hardware to transmit-on-sample, which will not wait until a certain interval to sample and transmit. Thus the sample rate may vary with real-time connection rate. Eventually, the data transmitted to mobile devices is not evenly sampled. But as the timestamp at each sample is preserved, in the resolution of the above issues, we choose cubic spline interpolation to (i) recover the saturation gap to a spike, (ii) resample the time series with an even time gap, and (iii) up-sample the time series to a higher sample rate. An example of cubic spline interpolation result is shown in Fig. 6b. Before interpolation, the raw data samples have a length of 200 and a sample rate of 100Hz. After interpolation, each sample has a length of 1000 and a sample rate of 500Hz. Performance gain from cubic spline interpolation compared to linear 1-D interpolation is shown in Sec. 6.3.1.

5.1.4 Data Input for Machine Learning: After segmentation and interpolation, we prepare data to feed to machine learning algorithms. The input data segments contain 2000ms of racket motion captured by the IMU, including 1000ms prior to ball impact and 1000ms afterward. Such a span of sampling preserves complete information of a stroke including player swing, follow-through, and ball impact. The segmented, interpolated IMU data contains 6 channels of IMU reading including *accelerometer x/y/z* and *gyroscope x/y/z*, with a length of 1000 sample points and sample rate of 500/s.

5.2 Ball Speed Estimation

To examine possible approaches to estimating tennis ball speed, we first looked at the physical basis of the energy transfer between the racket and ball at impact. Based on the conservation of momentum [71] and coefficient of restitution [69], a simplified physical model to represent the relationship can be:

$$E = M \cdot (v_{r-end} - v_{r-init}) + m \cdot (v_{b-out} - v_{b-in}) \tag{1}$$

In this system, E is the momentum of the racket before the impact, which is linearly proportional to the accelerometer reading that is perpendicular to the racket face [74]. M and m are the mass of the racket and the ball. v_{r-init} is the racket speed before impact and v_{r-end} is the racket speed after impact. v_{b-out} and v_{b-in} are the incoming and outgoing speed of the ball. For M and m, we can assume they are constants since we maintained the consistency of using the same type of racket and ball during the data collection. Another key equation is

$$COR = \frac{v_{b-out} - v_{r-end}}{v_{r-init} - v_{b-in}} \tag{2}$$

Where COR is the coefficient of restitution in racket and ball energy transfer. Using Eq. 1 we can substitute v_{b-in} from Eq. 3 while introducing COR. COR can be affected by several factors, including impact location and string tension, etc. In this case, v_{b-out} is our target value. The resulting representation of v_{b-out} is

$$v_{b-out} = \frac{COR}{1+COR} \cdot \frac{1}{m} \cdot (m \cdot v_{r-init} + E - M \cdot (v_{r-end} - v_{r-init}) + \frac{COR}{m} \cdot v_{v-end}) \tag{3}$$

In our approach, we did not fully attach to a physical model, where specific extrinsic factors like player mass and air drag, as well as intrinsic factors such as ball deformation and string extension, need to be considered for the model's optimal result. Instead, we used data-driven machine learning for speed estimation. This decision is based on the following rationale: (i) Building a fully-fledged physical model with all factors considered is computationally unfeasible for mobile and ubiquitous devices. (ii) The effort of quantifying factors that have minimal influence on results may not be proportional to the return of accuracy gain. (iii) We still reached a reasonable accuracy outcome without computing specifically the above factors, across a wide range of player mass, ambient environment, stroke styles, and racket types. The satisfied accuracy will be elaborated in Section 6.3. The scope of this study did not include those factors, but it remains a prospect for future work.

Table 3. Comparison of Machine Learning Algorithms for Speed Estimation

	Error				
Algorithm	**Mean**	**Median**	**Std Dev**	**Mean%**	**Median%**
CNN	7.89mph	5.94mph	10.79mph	19.33%	13.63%
Linear Reg	21mph	16.39mph	19.16mph	35.36%	30.91%
SVR	**4.81mph**	**3.59mph**	**5.03mph**	**9.89%**	**7.76%**
Polynomial Reg	9.56mph	7.27mph	8.58mph	19.80%	13.63%

To design the model that best adapts to this task, we implemented and evaluated multiple models, including Linear Regression, Polynomial Regression (degree=2), Support Vector Regressor (with 'rbf' kernel, penalty parameter C=10), CNN (2 Conv1D layer, two Fully Connected layers, with BatchNormand ReLU activation between layers). In our initial approach, as we assume that the outgoing ball speed can either be the collective effect of accelerations on all axes or rely on the force applied in the Z-axis direction, we employed Convolutional Neural Networks (CNN) and Linear Regression to predict the relationship between IMU readings and ball speed. However, despite extensive modifications to the structure and parameters, CNN consistently exhibited overfitting issues. Simultaneously, Linear Regression failed to achieve the required level of precision. Consequently, we explored alternative models, specifically Polynomial Regression and Support Vector Regression (SVR). Our hypothesis posited that the underlying relationship was too elementary for CNN yet too complex for Linear Regression. As delineated in Table 3, our comparative analysis of these machine learning models revealed that SVR outperformed the others, achieving an average error rate of 4.81mph, which corresponds to 9.89% of the average sample speed. Within the SVR framework, we experimented with various kernel functions, including linear, polynomial, sigmoid, and RBF (Gaussian), and identified the RBF kernel as the most effective in terms of overall performance. Results of detailed performance analysis of the SVM model are shown in Sec. 6.3.2.

5.3 Impact Location Detection

Since we are able to estimate the ball speed of strokes, we also considered the viability of detecting the impact location of the ball hitting the racket. Theoretically, different locations of ball impact should result in magnitude divergence on a particular axis of the IMU reading. e.g. If the impact location is at the far left side of the racket, a higher angular momentum is applied to the gyroscope y axis in the clockwise direction. Similarly, if the impact location is at the upper area of the racket, the rotation will appear on the gyroscope x axis in the clockwise direction. Such effect may combine if e.g. the impact location may be at the top left, and both gyroscope x and y axis will have variation. Fig.7 shows illustrations of the above cases. Furthermore, the principle of action and reaction, as articulated in Newton's Third Law, indicates that the reaction force from the ball when hit by a racket accelerated by the user's swing can also cause such racket rotation, meaning both the impact of the ball and the motion of the player's swing contribute to changes in racket angular velocity. However, the physical system of tennis ball impact also includes other artifacts such as hand force and inconsistent COR across the racket.

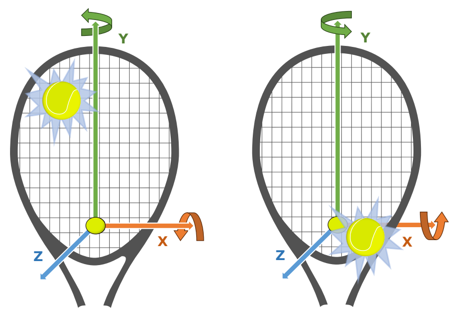


Fig. 7. Impact Location and Subsequent Gyroscope Axis Rotation

Constructing a comprehensive physical simulation surpasses the computational capabilities of mobile systems. Moreover, the current capability of motion sensors falls short of accurately detecting finer factors. To simplify the problem-solving process, we designed multiple machine-learning models to find the best fit for impact location detection. Initially, we endeavored to construct CNN models utilizing IMU data, which were processed via Short-time Fourier Transform (STFT). We employed STFT to leverage the feature dimension and information gain of IMU data. We also assume that unique impact location results in different angular and linear momentum variations for all axes, thus the complexity of CNN will fit this problem. However, it became apparent that STFT overly complicated the dataset, generating higher-order information that was challenging for CNN to interpret. Additionally, we encountered persistent overfitting and inference clustering issues with the CNN, despite various adjustments to its layers and parameters. This led us to pivot towards more straightforward machine learning models, including Linear Regression, Polynomial Regression, and Support Vector Regression. The overall accuracy for the experimented models is as shown in Table 4, including Linear Regression, Polynomial Regression (degree=2), Support Vector Regression (with 'rbf' kernel, penalty parameter C=10), Convolutional Neural Network(2 Conv1D layer, two Fully Conneted layers, with BatchNormand ReLU activation between layers). Our SVR model delivers the best accuracy, which achieves a median diagonal error of 3.03cm. In our analysis, it became evident that the issue extends beyond a mere linear complexity, as user movements and ball impacts simultaneously influence several IMU axes. When compared with Support Vector Regression (SVR) employing the Radial Basis Function (RBF) kernel, Polynomial Regression demonstrated inferior adaptability to data characterized by imbalance and high variability. Consequently, our SVR model emerged as the more favorable model among those we developed, owing to its superior adaptiveness and enhanced performance outcomes.

To achieve the prediction of impact location on the 2D surface of the racket face, we designed a combination of two SVR models to predict for x axis and y axis of the racket 2D face individually. To curtail the effect of COR variation, we proposed a method of data augmentation on ground truth at training time. The method can be formulated as:

$$C = C \times (1 + C * n) \tag{4}$$

where C is the coordinate on x or y axis, n is an amplification factor. We found the best accuracy gain when n=1 for x axis and n=2 for y axis. These values correspond to the aspect ratio of the racket face. We also found that several players have the habit of spinning their racket during tennis rallies, after which they may hit the ball using either side of the racket face. This situation led to another problem: *SmartDampener* needs to estimate the location of impacts that hit both sides of the racket. To resolve this issue, we implemented a classification model that distinguishes shots of the front side and the back side. The model is implemented with SVM and achieved an accuracy of 99.69% in 5-fold cross-validation and 99.52% in leave-one-subject-out validation. After the impact side is determined, we will invert the reading of the gyroscope x axis and accelerometer z axis for a back impact. We also inverted the accelerometer x axis, considering the possibility that the ball's incoming direction is not perpendicular to the racket face, resulting in displacements along y axis. All the above augmentation processes and models combine to be a pipeline for impact location detection. The performance result and evaluation of the impact location model are discussed in Sec. 6.3.3.

Table 4. Comparison of Machine Learning Algorithms for Impact Location

Algorithm	Mean Diagonal Error	Median Diagonal Error	Std Dev
CNN	4.23cm	4.22cm	0.19cm
Linear Reg	20.27cm	15.33cm	26.71cm
Polynomial Reg	5.60cm	4.87cm	3.70cm
SVR	**3.44cm**	**3.03cm**	**2.22cm**

5.4 Stroke Classification

To approach the problem of stroke classification, we first looked at the user's motion when making different strokes. we noticed that the player's motion of racket swings is distinct among various stroke types. Fig.8 is an example showing the difference in player action between Forehand Groundstrokes and Backhand Groundstrokes. We believe such divergence of motion can be used in the classification of strokes. Thus we choose machine learning methods to approach this problem. Existing works and tennis sensor products usually categorize strokes into three types: Serve, Groundstroke, and Volley. We further categorize tennis strokes into 6 types: Serve, Forehand Groundstroke, Backhand Groundstroke, Forehand Volley, Backhand Volley, and Overhead. We encoded the 6 different classes into labels of 0 to 5. We designed various types of machine learning models, using the feature map that pre-processed in 5.1 as input. To adapt our model to players with a left dominant hand, we swapped Forehand Strokes and Backhand Strokes, which we observed have opposite directions of motion compared to right dominant hand players.

As highlighted in this section earlier, our investigation revealed distinct variations in player movements across different stroke types. Consequently, it is imperative to utilize the entire time series of IMU readings to accurately identify the stroke type. This requirement dictates that our proposed model must effectively capture the temporal relationships between successive sensor data frames. Additionally, the model needs

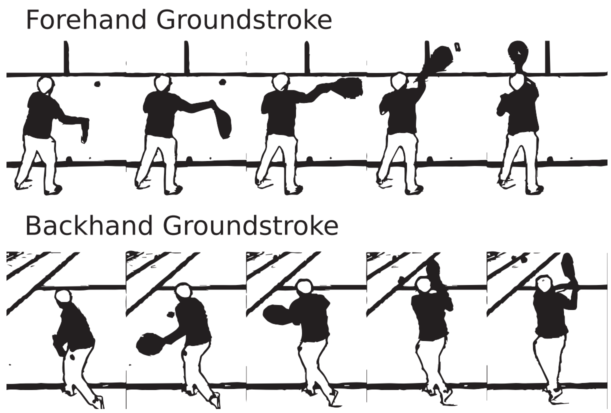


Fig. 8. Player Motion of Forehand Groundstroke and Backhand Groundstroke

to be adaptable to the varying speeds at which strokes are executed, encompassing both rapid and slower stroke completions. To implement the stroke classification model, we designed several models employing machine learning techniques, which include: AdaBoost, Random Forest, SVM, CNN. Initially, our approach involved the use of CNN and Random Forest, the latter being recommended for this specific task in [74]. However, our findings indicated sub-optimal performance from the Random Forest model, likely attributable to variations in sensor placement compared to the referenced study. We experimented with CNN because their complexity is sufficient to accommodate the temporal elasticity of a swing caused by differing swing speeds. While CNN demonstrated promising precision, we observed inconsistencies in its performance, particularly when predicting for users that were not included in the training set. To enhance accuracy across a diverse range of players and stroke speeds, we expanded our model exploration to include other potential methods like Adaboost and SVM. Table. 5 demonstrates the following models: AdaBoost with Decision Tree base model, AdaBoost with Random Forest base model, Random Forest (max_depth=50), SVM (with 'rbf' kernel, penalty parameter C=10), CNN (2 Conv1D layer, two Fully Connected layers, with BatchNorm, with Dropout=0.8 and ReLU activation between layers), our SVM model exhibited superior accuracy in stroke classification, culminating in an impressive overall accuracy rate of 96.75%.

We also propose and validate that domain adaptation can further improve the accuracy of the model with a minimal amount of adaptation data for unseen users. The performance comparison of our models and detailed evaluation of SVM are presented in Sec. 6.3.4.

Table 5. Comparison of Machine Learning Algorithms for Stroke Classification

Algorithm	Precision	Recall	F-1 Score
AdaBoost (Decision Tree)	87.24%	89.39%	88.08%
AdaBoost (Random Forest)	87.29%	89.43%	88.14%
Random Forest	87.71%	89.41%	88.13%
SVM	**96.48%**	**96.75%**	**96.61%**
CNN	92.34%	93.05%	92.65%

6 PERFORMANCE EVALUATION

We discussed the evaluation of *SmartDampener* performance in this section. Discussion of our user study and dataset is in Sec. 6.1.1. Introduction of data collection methodology is in Sec. 6.1.2. Then we explain the implementation in Sec. 6.2. After that, we evaluate the performance of ball speed calculation in Sec. 6.3.2, impact location detection in Sec. 6.3.3, and stroke detection in Sec. 6.3.4. Finally, we evaluate the overall performance of *SmartDampener* in Sec. 6.3.5.

6.1 User Study

6.1.1 Data Set

Our study has been approved by the IRB committee. We conducted a study with 15 players (10 males, and 5 females). The players are aged between 20-50 and weigh between 50-90 kg. The users wear the sensor device as shown in Fig. 9 with the sensor snugly fitted on the tennis racket. Players were instructed to simply slide it onto the strings of the racket until it sat securely in the desired position, as shown in Fig. 9, akin to the traditional mounting method of tennis dampener. We divided the subjects into three proficiency levels: beginner, intermediate and advanced. The beginner has played tennis for 0-2 years, intermediate players have played for 3-5 years and advanced players have played for more than 5 years. The players were then instructed to play with the tennis racket which was mounted with *SmartDampener* in two user study sessions, one was for stroke type/ball speed and another one was for impact location. To incorporate all ranges of possible playing behavior, players were instructed to play naturally and where possible perform stroke types including serves, forehand groundstroke, backhand groundstroke, forehand volley, backhand volley, and overhead (based on literature [3]). Because the ground truth of impact location is different from the ground truth of speed and stroke type, we conducted two different methods of data collection. The details of these two user study sessions are presented below.

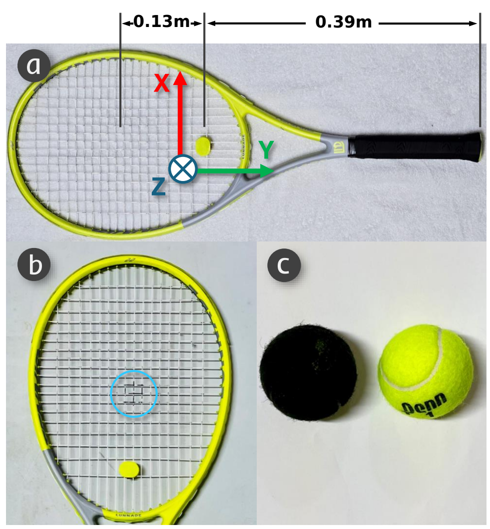


Fig. 9. (a) Sensor Placement and coordinate system (b) Stencil ink marked by ball impact (in red circle) (c) Tennis ball with stencil ink (left) and without stencil ink (right)

6.1.2 Data Collection Methodology

Stroke Type and Ball Speed: Each pair of users took 3 breaks with removing and remounting the sensor device in between and the total study time per pair of users is two hours. While *SmartDampener* provides IMU data for stroke type and ball speed, the SwingVision serves as ground truth for validation as well as provides labels of stroke type and ball speed for training *SmartDampener*s data analysis model. SwingVision, an advanced camera-based solution tailored for tennis, provides stroke type and speed, yet it lacks the capability to precisely determine impact location. Since there is no previous data collection methodology for tennis ball impact location, we devised a novel approach inspired by the data collection methodologies utilized in a badminton impact location study [66]. We will discuss the data collection method of tennis impact location later. For speed and stroke type, we collected a total of 5526 data points, including 1765 serves, 2626 forehand groundstrokes, 978 backhand groundstrokes, 87 forehand volleys, 55 backhand volleys, and 15 overhead.

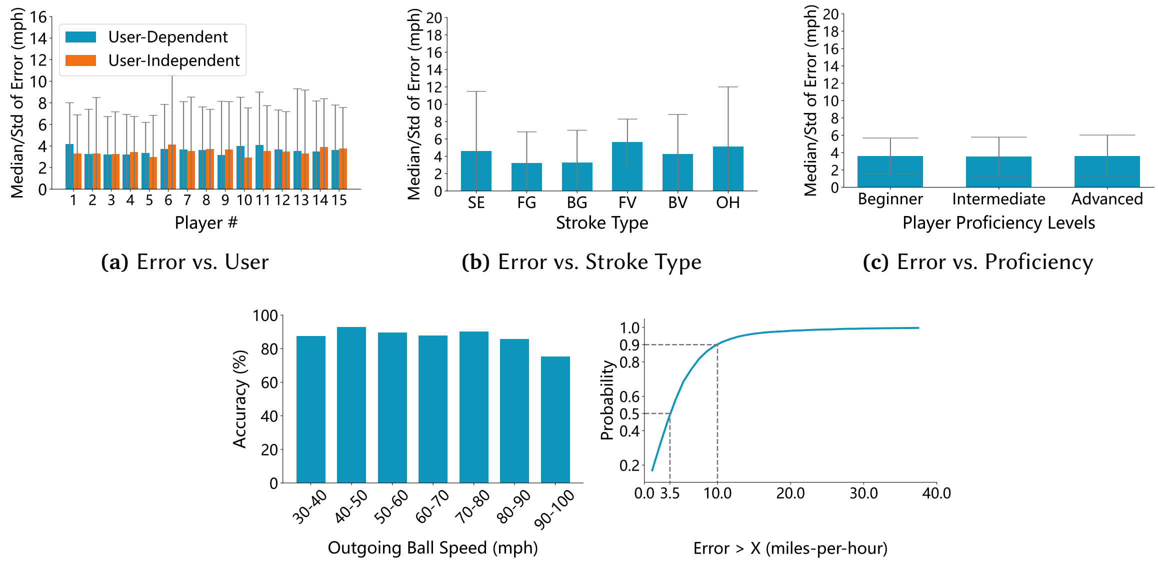
Impact Location: Since there is no previous work for tennis ball impact location tracking using sensor-embedded dampeners and SwingVision can not provide impact location, we devised a novel data collection approach inspired by [52]. Each player participated in 6 separate sessions with each session lasting for 30 minutes. Each pair of users took a break with removing and remounting the sensor device between each session and the total study time per pair of users is three hours. The tennis ball was sprayed with stencil ink prior to each trial, as shown in Fig. 9c. To facilitate this method, we installed 50 lbs white strings on the rackets. After each trial, the tennis racket faced with an inked impact location was photographed as the ground truth of impact location as shown in Fig. 9b. The impact location was then manually labeled with a utility which we designed with Python[65] and OpenCV[32] library. The racket face was cleaned up after each trial and balls were replaced every 50 trials to avoid the weight gain from ink build-up. For impact location, we collected 3328 data points in total.

6.2 Implementation

SmartDampener is implemented on a combination of desktop and smartphone devices. The CNN model is implemented with PyTorch library[58] and other ML models are implemented with Scikit-Learn [59] library, and the training is implemented on a desktop with Intel Core i7 9700K CPU, 48GB RAM, and NVIDIA RTX 3080 GPU. Once trained, the inference is performed entirely on smartphones (Samsung S20 and OnePlus 9 Pro) using ONNX Runtime [31].

6.3 Performance Results

To evaluate the performance of *SmartDampener*, we conduct analysis on the following aspects: ■ Segmentation and Interpolation. ■ Stroke type classification. ■ Ball speed estimation. ■ Impact location detection In each part, we conducted user-independent analysis and multi-aspect comparison and evaluation. To evaluate the performance of *SmartDampener*, we provided a baseline comparison with the performance of state-of-art work. For ball speed estimation and stroke type, we choose the accuracy of TennisEye [74] as the baseline. TennisEye is a state-of-art sensor-embedded solution of estimation speed and stroke type. *SmartDampener* achieves estimation of ball speed with a median error of 3.59 mph, in percentage is 9.89%, better than the accuracy of ball speed of TennisEye with an error of 5.6 mph, in percentage is 10.8%. *SmartDampener* achieves estimation of stroke type with an overall accuracy of 96.75%, better than the accuracy of stroke type of TennisEye with an overall accuracy of 96.2%. Since *SmartDampener* is the first design of a sensor-embedded smart dampener capable of providing insights of impact location, there is no baseline for estimation of tennis impact location. One potential off-the-shelf competitor we



(a) Error vs. User **(b)** Error vs. Stroke Type **(c)** Error vs. Proficiency

(d) Accuracy vs. Ball Speed **(e)** CDF of Speed Error

Fig. 10. Evaluation of Speed Estimation Model

can find is the Zepp Tennis sensor. However, as of when this research is conducted, the companion mobile application of Zepp is no longer accessible. Thus, it is unable to determine the performance of the Zepp Tennis sensor through either experiment or other reliable sources.

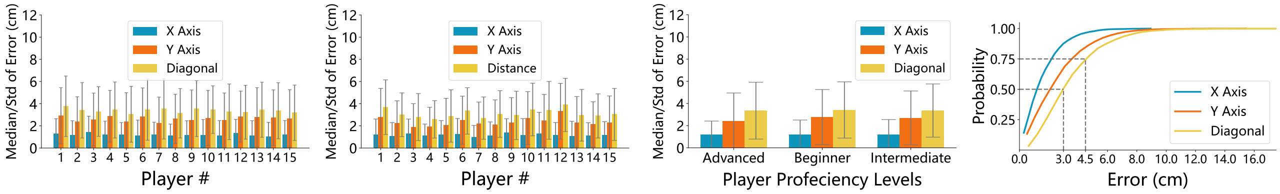
Table 6. Comparison of Final Accuracy with Cubic Spline Interpolation and 1-D Linear Interpolation

Interpolation	Ball Speed Error	Stroke Type Error	Impact Location Error
Interp1D	12.39%	5.83%	3.72cm
Cubic Spline	9.89%	3.25%	3.30cm
Δ	**-2.58%**	**-2.31%**	**-0.42cm**

6.3.1 Stroke Segmentation and Interpolation Our stroke segmentation methods described in 5.1 reached an average accuracy of 96.69% across all our samples, meaning near-to-no strokes will be missed for analysis during tennis gameplay. We also calculated the performance gain with the use of cubic spline interpolation, as compared to a linear 1-D interpolation with the same output length. The performance leverage of cubic spline interpolation on the stroke analysis is shown in Table 6

6.3.2 Ball Speed Calculation Accuracy

Overview: As previously presented in Table. 3, the SVR model that we designed achieves a median error of 3.59mph, in a percentage of 7.76%. Compared to similar works in tennis ball speed estimation, the physical model proposed in TennisEye[74] achieved an overall error of 10.8%. Fig. 10e shows the CDF of ball speed estimation error. At the 50th percentile, the error is 3.5mph, at the 90th percentile the error is 10mph.



(a) Error vs. User **(b)** Error vs. User Independent **(c)** Error vs. User Proficiency **(d)** CDF of Error

Fig. 11. Evaluation of Impact Location Detection Model

Accuracy vs. Users: We conducted a user study for ball speed estimation among 15 users. As shown in Fig. 10a, in the 5-fold cross-validation, *SmartDampener* is able to contain the median error between 3.15mph and 4.10mph for all players. In the leave-one-subject-out cross-validation, players can still have median errors of <4.12mph in all cases, which means the speed estimation model of *SmartDampener* can adapt to unseen players without perceptible loss of precision. Fig. 10c also showed that *SmartDampener* can achieve a stable <3.61mph across all player proficiency levels.

Accuracy vs. Stroke Types: We present the ball speed estimation performance of *SmartDampener* under the following stroke types: Serve(SE), Forehand Groundstroke(FG), Backhand Groundstroke(BG), Forehand Volley(FV), Backhand Volley(BV) and Overhead(OH). The speed estimation models perform the best with Forehand Groundstroke, Backhand Groundstroke. For these strokes, the speed estimation achieved a median error of less than 3.29mph, as shown in Fig. 10b. For other stroke types, the error still resides between 4.48mph and 5.60mph. We believe that, for Forehand Groundstroke and Backhand Groundstroke, the performance of *SmartDampener* is better as a result of their higher population in our training sample. In tennis, Groundstrokes are the most prevalent strokes [46]. The accuracy can be further improved with more training samples for particular stroke types.

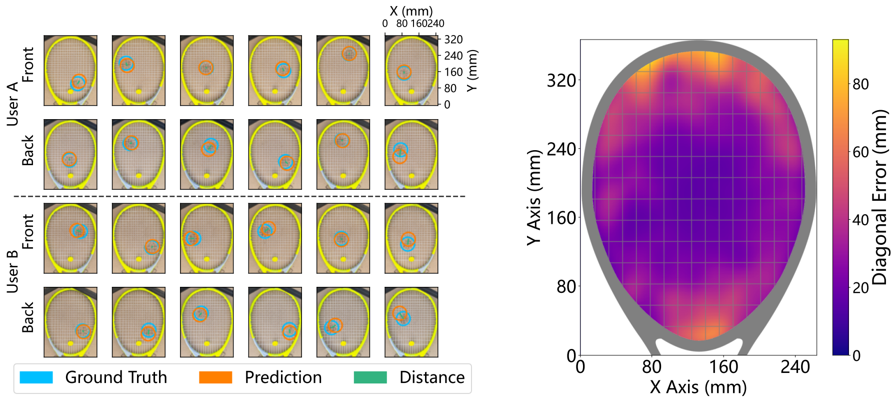
Accuracy vs. Speed. We presented Fig. 10d to show that in most speed ranges, *SmartDampener* can achieve an accuracy of >90%. We observed slightly lower accuracy for samples in higher speed ranges. We assume the reason can be the lower population of high-speed samples in our training data set. Typically, only professional players can make consistent high-speed strokes. In most tennis rallies, the outgoing ball speed from a stroke is mostly seen between 30mph and 80 mph[49].

6.3.3 *Ball Impact Location Detection Accuracy.*

Overview: Previously in Table 4, the best accuracy delivered by SVR achieved a median diagonal error of 3.30cm. This result is as small as the width of 3 sectors of string grid on common tennis rackets.

Front Back Classification: The classification model we designed to determine the front/back side of impact achieved an accuracy of 99.69% in 5-fold cross validation and above 98.0% for all players in leave-one-subject-out validation.

Accuracy vs. Users: Depicted in Fig. 11a, *SmartDampener* achieves stable accuracy across all players with minor variations. In the 5-fold cross-validation, the error of individual players can be as low as 3.04cm and the difference of error between users varies in a range of no more than 0.7cm. As demonstrated in 11c, *SmartDampener* maintained consistent accuracy among players of differing expertise. Therefore,



(a) Impact Location Result Examples **(b)** Distribution of Error

Fig. 12. Visualization of Impact Location Detection Result

we believe *SmartDampener* can estimate impact location across players with consistent accuracy with diversity in gender, body masses, sizes, player proficiency, etc.

Qualitative Result: Fig. 12a depicts the qualitative results of impact location estimation. In Fig. 12a and all other evaluations in this section, we are using a racket with a width of 26cm and a height of 35cm. This paper also includes a demo video, url pointing to the demo video is provided at [15]. We compare the estimation of impact location with the ground truth imprinted by stencil ink on the racket, as discussed in Sec. 6.1. Fig. 12b shows the distribution of impact location detection error across different zones on the racket. Evidently, *SmartDampener* is capable of estimating impacts across a wide range of locations on the tennis racket with decent accuracy. We believe that these results are promising in the context of a wide range of applications of sport analysis. We also observed slight accuracy decay when the impact location is closer to the racket frame. We believe that is because (i) COR varies from racket center to frame and (ii) We have relatively less population that falls adjacent to frame in our samples.

User Dependent vs. User Independent: We performed leave-one-subject-out validation across the players in our samples and the performance result is shown in Fig. 11b. All 15 players' median errors are contained between 2.60cm and 3.88cm. Over half of the users have errors of less than 3cm. In that case, we believe *SmartDampener* is capable of impact location estimation even on unseen subjects, delivering similar accuracy to user-dependent results even for new players.

6.3.4 Stroke Classification Accuracy

Overview: As previously shown in Table. 5, we achieved an overall accuracy of 96.75% with SVM. Compared to other works, we achieved similar stroke classification accuracy as TennisEye[74] (96.2%). However, TennisEye only has 3 stroke types while we have 6.

Accuracy vs Users: Shown in Fig. 13a, the stroke classification implemented with *SmartDampener* achieved accuracy between 99.25% and 90.0% across all 15 players in a 5-fold validation on the SVM model. We also presented the accuracy distribution among different player proficiency in Fig. 13c, which displays above 95.03% accuracy for all player proficiency levels from beginners to professionals. We believe that *SmartDampener* can classify tennis strokes with a stable accuracy for players of different proficiency, age, gender, body weight, etc. Additionally, in Fig. 13a we have Player 5 being a right-dominant-hand user. On this player, *SmartDampener* showed equally high performance as it showed on other players, which means *SmartDampener* can adapt to players with different dominant hands.

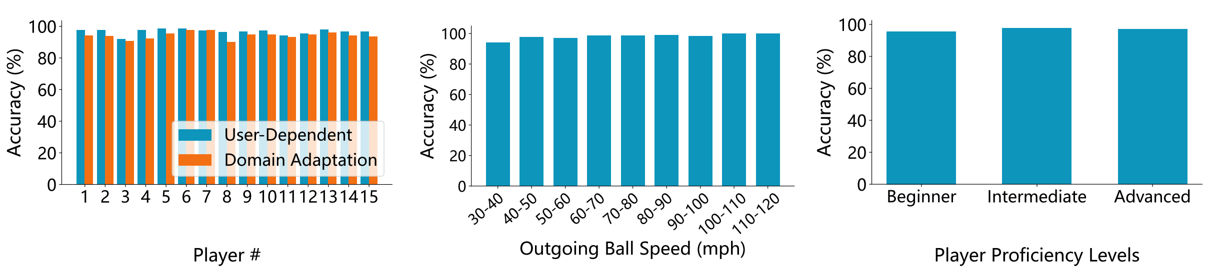
Accuracy vs Speed: According to Fig.13b, *SmartDampener* shows a stable accuracy of above 93.85% for stroke classification across a wide range of speeds. This means *SmartDampener* can achieve a consistently high accuracy under different game-play intensities to classify strokes.

Domain Adaptation: Fig.13a also showed evaluation results of multi-user models with domain adaptation. We implemented user adaptation for the multi-user model of stroke classification with 30 user-specific data samples for each user, based on each model that is pre-trained in the leave-one-subject-out cross-validation. From Fig.13a we are confident that with an insignificant amount of user-specific data, *SmartDampener* can achieve stroke classification accuracy that is similar to the user-dependent result for unseen players.

6.3.5 SmartDampener *Performance*

■ **Usability Study:** To assess the user experience of SmartDampener, an extensive usability study was conducted. The study aimed to achieve the following objectives: (i) to conduct a comparative analysis of SmartDampener against alternative sensing platforms, considering factors such as community acceptance, weight, and ease of use, (ii) to investigate the mounting experience of *SmartDampener* compared with traditional tennis dampener, (iii) to investigate how users were satisfied performance of *SmartDampener*, and (iv) to explore users' understanding and interpretation of stroke type, ball speed, and impact location facilitated by SmartDampener. We asked users who participated in the usability study to complete a questionnaire on their experience with *SmartDampener* once the user study experiment (which is discussed in Sec. 6.1) was complete. The questionnaire was designed to solicit feedback on users' experiences with SmartDampener. The questionnaire encompassed inquiries aligned with the aforementioned objectives. Detailed instructions elucidating each objective will be provided subsequently.

■ **User Experience in Comparison with Existing Wearable Platforms:** Fig. 14 depicts the results of user experience on *SmartDampener* compared with three alternative sensing platforms. To compare the user experience among these platforms, each player used all four platforms separately. We compared *SmartDampener* with the other three platforms, including TennisEye [74], wrist-mounted sensor, and Zepp [25]. Note that we only created a dummy prototype of TennisEye based on the size and weight specification in the paper because the design details of the platform are not fully available to the public. Participants rated all devices anonymously based on *community acceptance*, *weight*, and *easy to use* from 0 to 10. The higher the rating, the better the usability of the device. The wrist-mounted sensor turned out to be rigid and not easy to use for a long time, while TennisEye and Zepp received a higher rating than



(a) Accu. vs. User **(b)** Accu. vs. Ball Speed **(c)** Accu. vs. Proficiency

Fig. 13. Evaluation of Stroke Classification Model

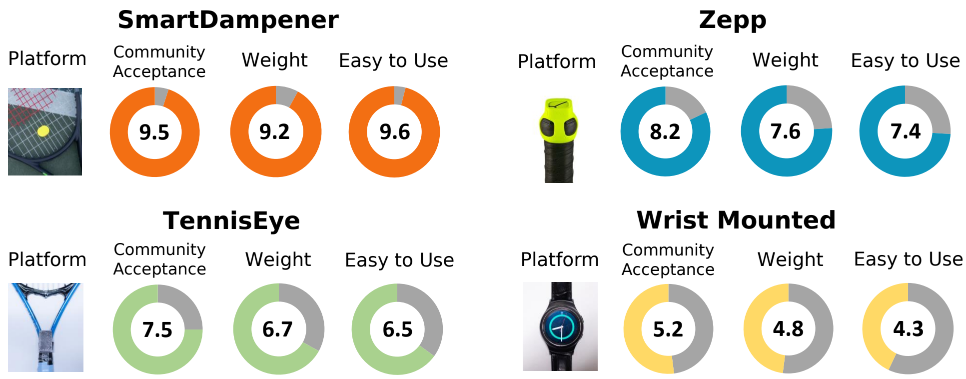


Fig. 14. User experience survey on *SmartDampener* compared with three alternative sensing platforms

the wrist-mounted sensor. However, with TennisEye and Zepp, the players noticed that these platforms modified either the weight or length of tennis rackets, thus making them a bit uncomfortable. *SmartDampener* secured the highest scores in community acceptance, ease of use, and weight shown in Fig. 14. We envision *SmartDampener* can gain ubiquitous acceptance within the tennis community.

■ **User Experience on Mounting Instruction:** To evaluate the user experience of mounting *SmartDampener*, users were instructed to simply slide it onto the strings of the racket until it sits securely in the desired position akin to traditional installation methods observed with real tennis dampeners. Afterward, they were asked to compare the similarity of the mounting of *SmartDampener* with the mounting of a traditional dampener. About 92% of the participants considered mounting of *SmartDampener* similar to a traditional tennis dampener, whereas the remaining 8% users noted that the *SmartDampener* needs to be recharged periodically, thus making it slightly more effort to use it in comparison with traditional dampeners.

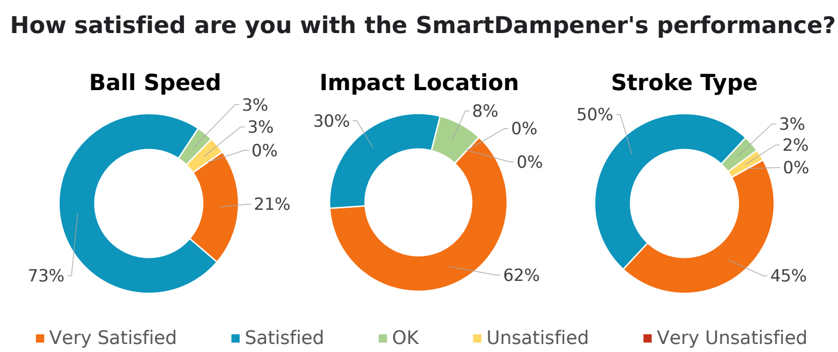
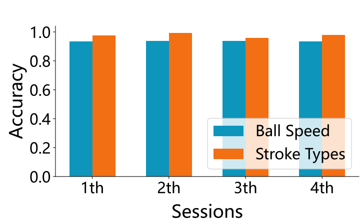


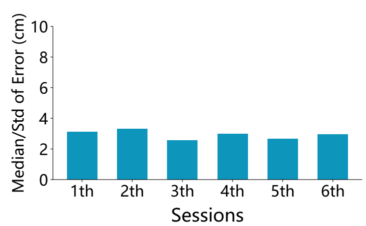
Fig. 15. User Experience Survey on *SmartDampener* Satisfactory

■ **User Experience on Satisfaction of Tennis Metrics Determined by *SmartDampener*:** To investigate how users were satisfied by the performance of *SmartDampener*, we asked participants (tennis players and tennis coaches) who participated in the study to complete a questionnaire on their experience with the *SmartDampener*. The survey included questions on the users' perspective of *SmartDampener*'s performance regarding stroke types, ball speed, and impact location. Regarding the rating scale of *SmartDampener*'s performance, we used a rating scale from 1 to 10 corresponding with "Very Unsatisfied" to "Very Satisfied". As shown in Fig. 15, more than 94%, 95%, and 92% of the users reported that they were satisfied with the performance of *SmartDampener* regarding stroke type, ball speed, and impact location. Considering that we will open- source *SmartDampener* to the community, we anticipate that its accuracy will exhibit enhancement as a result of increased data availability and community contributions in the future. Overall, users were satisfied by the accuracy particularly given that *SmartDampener* is low-cost and embeds sensors in a popular tennis accessory in the form of a dampener. The alternatives such as cameras either cannot track metrics such as impact location, or come with a high-cost barrier and installation/maintenance overheads.

■ **Experience in Interpreting Data from *SmartDampener*:** To investigate how users can interpret stroke type, ball speed, and impact location, we conducted interviews with participants who have participated in the user study. After conducting interviews with tennis players regarding their interpretation of data from *SmartDampener*, we had several key observations. Using stroke type, participants assessed their stroke selection and versatility on the court by understanding stroke type. For example, participants became more cognizant of their strengths and weaknesses with respect to stroke selection and could try to dedicate more time in training towards improving weaker parts of their game. Using ball speed, participants could understand how much power is behind their shots, which helps them to fine-tune their strength and control. For example, a shot with high speed has to be given sufficient topspin to keep it inside the court. Using the impact location, participants could evaluate the precision of each shot. Hitting the ball with the sweet spot [33, 34, 40] on the racket is shown to improve the accuracy of shots, and users believed they can use the impact location feature of *SmartDampener* to train with hitting on the sweet spot of the racket. Overall, participants agree that metrics such as stroke type, ball speed, and impact location can improve their game.



(a) Speed and Stroke Acc. vs. Sessions



(b) Impact Location Accu. vs. Sessions

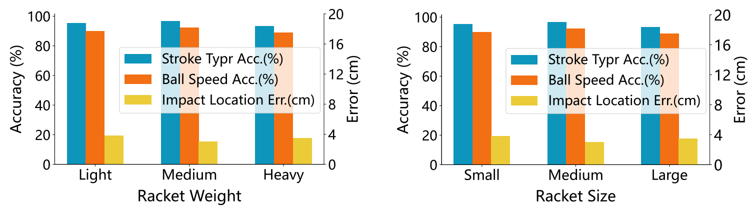
Fig. 16. *SmartDampener* Performance vs Sessions

Robustness to Sensor Placement: The variations in accuracy of stroke, impact location, and speed across different sessions are steady as depicted in Fig. 16. In each session, the sensor device was removed and remounted across sessions thus helping evaluate any effects of changes in sensor position with respect to players' habits when playing tennis with a real dampener. The accuracy is stable across various sessions because any minor variation in position across sessions is very small, compared with the hardware noise floor. Therefore, the impact of sensor placement on the accuracy of stroke, impact location, and ball speed is negligible.

Robustness to Ball Hit: Table. 7 depicts the performance of *SmartDampener* under ball-hitting conditions. To determine the reliability of the mechanical design of *SmartDampener* under ball-hitting, we conducted studies with 15 players in real play scenarios. Users are instructed to allow a tennis ball to make contact with the sensor. The results are depicted in Table. 7. As observed, the accuracy of performance of

Table 7. Performance of *SmartDampener* under Ball-hitting Conditions (Error, Mean)

Tasks	Not Hitted	Hitted
Speed	4.81mph	4.96mph
Impact Location (Diagonal)	3.44cm	3.62cm
Stroke Type	3.25%	4.12%



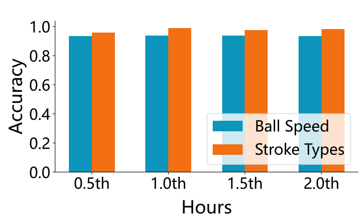
(a) Performance vs. Racket Weight (b) Performance vs. Racket Size

Fig. 17. *SmartDampener* Performance vs Rackets

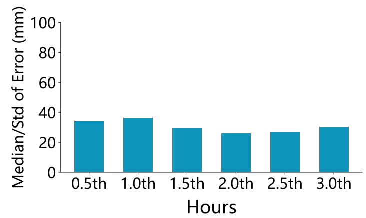
SmartDampener does not degrade under ball-hitting conditions. Therefore, the accuracy of stroke, impact location, and ball speed is robust under ball-hitting conditions.

Robustness to Racket Diversity: To validate the impact of different weights on tennis rackets, we conducted a supplemental user study with various additional rackets. In total, we have rackets of three different weights (270g, 285g, 315g), and three different sizes (100in^2, 103in^2, 110in^2), which cover the majority of racket diversity in the real world[4, 5, 11]. In the supplemental user study, the users are instructed to use the rackets as mentioned above in real play. The models are trained using the large dataset collected previously using a racket of medium weight and size. For evaluation, the models are tested against a newly gathered dataset that includes data from different types of rackets. The resulting accuracy of ball speed, stroke type, and impact location is depicted in Fig. 17a and Fig. 17b. Our findings indicate that the performance of *SmartDampener* on rackets with varying weights(light and heavy) and head sizes(small and large), without explicit domain knowledge, was comparable to its performance on rackets of medium weight and size, whose training and validation is upon same knowledge domain. We attribute the consistency in performance to the relatively stable differences in weight and size across various racket types. As defined in [5], the weight and size of rackets fluctuate by approximately 10% between different classes. Thus the physical characteristics of rackets may not exhibit perceptible influence on *SmartDampener* performance. In future works, it is also possible to further improve racket adaptability and overall accuracy by (i) open-sourcing *SmartDampener* for the community to increase dataset amount and diversity and (ii) specifying racket parameters in models.

Lifespan of *SmartDampener*: According to a statistic we performed on the impact location dataset, the average frequency of *SmartDampener* being hit is 1.2/h. An average professional tennis player may play approximately 1300 hours a year. Accordingly, the approximate number of times the *SmartDampener* will be hit by balls is 1560 (1.2 times hourly and for 1500 hours). We conducted a durability test on the system hardware by placing a tennis ball launcher against a fixed racket with *SmartDampener* equipped. The system hardware is hit by machine-launched balls repeatedly for over 1500 times. Afterward, the system still functions as before the experiment, the nature of IMU readings, noise distribution, and vibration



(a) Speed and Stroke Accu. vs. Time



(b) Impact Location Accu. vs. Time

Fig. 18. *SmartDampener* Performance vs Continuous Use Time

dampening was similar to that before. This indicates that the durability of the *SmartDampener*'s sensor would be at least 12 months with respect to handling impacts from the ball. The actual lifespan could be higher because we did not find any measurable degradation due to impacts. The electronic components in *SmartDampener* are similar to other products like Apple Airtag [9] that have high durability. The casing material in *SmartDampener* (TPU) is also widely used in sports equipment such as shoe out-soles [1]. Thus we believe *SmartDampener* system is durable. In the future, since our platform will be open source, its durability and lifetime over a much longer duration (decades) can be further validated by the community with more experiments and data collected using our platform.

Power Consumption and Latency: The power consumption of the sensor device itself is discussed in Sec. 3.2. Here, we analyze the power consumption of executing analytic models in *SmartDampener* on smartphone devices, using Batterystats and Battery Historian [29] tools to profile the energy of the analytic models model. The latency of execution of all analytic models models together on Samsung S20 and OnePlus 9 Pro are around $60ms$ for both devices, sufficient for real-time applications. The real-time power discharge rate of *SmartDampener* implemented on the smartphone is 6.08% and 5.25% per hour for Samsung S20 and OnePlus 9 Pro, with a duty cycle of one execution every 2.5 seconds, simulating the interval of real tennis rally.

Longer Session Experiment: To study long-term effects like potential drifts, we conducted studies under real play conditions with 15 players for 2 hours for stroke types classification and speed estimation and 3 hours for impact location. Players continuously used the tennis racket equipped with *SmartDampener*. We conducted a 30-minute session as per our user study protocol described earlier. As depicted in Fig. 18, the accuracy of *SmartDampener* does not degrade with time because *SmartDampener* does not integrate long-term sensor data.

7 DISCUSSION AND FUTURE WORK

Extensibility of *SmartDampener* to Incorporate Additional Sensors: This paper shows the feasibility of estimating ball's speed, impact location, and sweet spot and stroke type via vibration captured by the IMU sensor embedded in the current design of *SmartDampener*. However, we believe we have only begun to explore the potential of the design. *SmartDampener* can incorporate additional sensors such as acoustic and camera for applications in spin tracking and slice angle estimation. While integrating all sensors in a single dampener might be limited by the current space and power consumption, we are exploring these potentials and hope to extend the platform to new possibilities.

Adaptability of *SmartDampener* to Various Sport Applications: While we focus on the tennis sport application in this paper, we believe *SmartDampener* is extensible to application in various sports applications such as field tracking and athlete analytics due to the lightweight design and small size form factor. For example, attaching *SmartDampener* to the clothes of athletes enables the monitoring players' physical load and fatigue. Monitoring players' physical load and fatigue can protect them from injuries.

Human Body Pose Detection: *SmartDampener* shows the feasibility of tracking players' stroke types while estimating the ball's characteristics. Motivated by promising results, we plan to explore full-body motion tracking using *SmartDampener*. Particularly, we are interested in measuring motion segmentation and position information.

8 CONCLUSION

SmartDampener shows the feasibility of estimating ball's speed, impact location, sweet spot, and stroke type with a design of a smart dampener in a native form factor, low cost ($\approx$ \$10), and long battery life. IMU is embedded within *SmartDampener* to enable a wide range of applications in sports analysis. A user experience study of the *SmartDampener* is conducted that indicated the acceptability and popularity of *SmartDampener* in the tennis community. To evaluate the sensing capabilities of *SmartDampener*, an extensive study with 15 users provides an error of 3.59mph in speed, 3.03cm in impact location, and an accuracy of 96.75% in six stroke types recognition. Despite progress, we believe we have only begun to explore the research possibilities of *SmartDampener*. A number of applications in the area of sports training, mixed reality in sports, performance monitoring, injury prevention, and extensibility to other sports can be explored. We believe the community can expand *SmartDampener* with additional hardware and software capabilities.

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