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Exploring the Application of Machine Learning in Saliva Sensing for Real-Time Health Monitoring

Amit Sharma[1*], Beemkumar Nagappan[2], Nipun Setia[3], Yuvraj Parmar[4], Vijay Jagdish Upadhye[5], and Pavan Chaudhary[6]

[1*]School of Computer Applications Lovely Professional University, Phagwara, Punja, India. profamitsharma@gmail.com, https://orcid.org/0000-0003-1451-5892

[2]Department of Mechanical Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bangalore, Karnataka, India. n.beemkumar@jainuniversity.ac.in, https://orcid.org/0000-0003-3868-0382

[3]Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India. nipun.setia.orp@chitkara.edu.in, https://orcid.org/0009-0005-8635-6802

[4]Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh, India. yuvraj.parmar.orp@chitkara.edu.in, https://orcid.org/0009-0007-1619-9885

[5]Department of Microbiology, Research and Development Cell, Parul University, Vadodara, Gujarat, India. vijay.upadhye82074@paruluniversity.ac.in, https://orcid.org/0000-0002-8821-1720

[6]Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh, India. chaudharycaracf6@gmail.com, https://orcid.org/0009-0000-7596-2341

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Abstract

Here, we discuss some machine-learning applications that support saliva sensing for real-time health monitoring. Saliva has been identified as a promising non-invasive diagnostic gateway for various types of biomarkers, which is readily available in numerous pathological conditions. Data analysis, pattern discovery, and prediction and classification tasks are some of the important fields in which machine learning techniques have had the most success. For instance, in the context of saliva sensing, machine learning algorithms can aid in performing efficient analysis of the multi-dimensional nature of saliva data and complex elements associated with it, enabling the detection of the slightest variation in biomarkers that may be indicative of certain health conditions. Yet, the most potential in salivary sensing is likely to be in the early identification and monitoring of diseases such as diabetes, cancer, and infectious diseases by machine learning models. Say the algorithms are trained on saliva samples, for example. In this case, they would learn to recognize patterns of saliva that correspond with specific health issues and accurately diagnose them. Another idea is to build personal systems that monitor your health continuously and help screen for potential problems.

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*Corresponding author: School of Computer Applications Lovely Professional University, Phagwara, Punja, India.

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1 Introduction

Saliva-detecting technology is an inexpensive and noninvasive method for monitoring a person's health in real-time. It is these biomarkers present in the saliva, hormones, antibodies, enzyme(s), etc., that the identification and analysis of which affords us Information about the state of health of a person (Zheng et al., 2021; Khyade et al., 2017). Sample collection from saliva is easily accessible and can be carried out without any special training or instruments, making this method convenient and practical. Saliva Sensing Technology: Saliva Collection. The first step in saliva sensing technology is collecting saliva from the subject (Ji et al., 2022). Methods of collection may include spitting into a tube or using salvia kits for direct collection from the mouth. The saliva sample can be assayed in several ways, including colorimetric assays, as well as electrochemical and optical sensors (Soltani Zarrin, 2021; Bhaskar et al., 2023). Such methods can interface with specialized receptors or enzymes that specifically trap the corresponding target biomarkers present in the saliva and produce a distinguishable signal. This e-textile sensor is wearable in the proximity of a real-time health monitor, where the same aspect can be taken advantage of] in another way, designing a Salivary Sensing platform (Alhaddad et al., 2022) rm. Unlike blood collection, which occurs at specific points in time, saliva can be collected multiple times per day and potentially provides a more comprehensive assessment of one's health (Zhang et al., 2022). Given that saliva contains biomarkers such as those identified in other body fluids, such as blood, which can provide Information on the status of health, both in terms of diagnosis and also monitoring of chronic diseases, this makes it possible to monitor chronic diseases without the need for more taking invasive plasma or serum and is a less invasive matrix to collect noninvasive chronic disease biomarkers. Research in the area of saliva sensing technology is believed to be the most practical way to monitor well as diabetic management and infectious disease diagnosis, which can impact healthcare. This will enable individuals to monitor their health on the go and act sooner to prevent diseases. It can also be useful in the development of personalized interventions and in improving disease treatment. However, several challenges still need to be addressed, including the usability of the saliva collection protocol, the sensor's sensitivity and specificity, and data analysis for the acquired data (Ember et al., 2022). As technology improves and we learn more about saliva-sensing tests, this format of health monitoring could be a game-changer for how we all strive to stay healthy. Saliva, as a contactless biological fluid, can be easily collected and detected rapidly and repeatedly, indicating that it is a promising approach for real-time health monitoring using saliva-sensing technology (Boopathy et al., 2024). As is the case with any new technology, several real-world technical challenges must be addressed to implement such a system. This paper will summarize the challenges of real-time health monitoring via saliva sensing and propose solutions. The main issue is that the sensor readings are not precise and reliable (Yadav & Chawla, 2025; Bhaskar et al., 2023). Saliva is a multifaceted fluid, and its volume and composition can fluctuate in response to a person's chronobiological rhythm, diet, hydration status, local factors, and workload. Some degree of variability in sensor values may occur, which can make comparison and analysis difficult. Analysis selection and detection - The selection and detection of the analysis are central technical questions. Assessing a multitude of biomarkers in non-invasively sampled saliva may be beneficial for gaining information about overall health status. It's a very difficult challenge to understand which family members are relevant and to develop a sensor that can identify and quantify these family members." For saliva sensors, the requirement is that the sensors are highly selective in discriminating the target biomarker from other chemicals (e.g., those of food origin) and, most importantly, highly sensitive in detecting minute quantities of the biomarker in saliva. The design and fabrication of the sensing device are described in Issue 3 (Nath et al., 2022; Khyade et al., 2017). We have a few requirements for the sensor: it needs to be small, user-friendly, and inexpensive. It should, fingers crossed, work for a reasonable amount of time before the battery craps out and be resistant to the elements, from the tundra and rain to temperature and humidity fluctuations. It needs to accumulate and store multiple samples over a prolonged period to be useful for long-term health monitoring. Third, as a technical hurdle, the input and output of the sensor can be interfaced with other devices and databases. Saliva Sensor Information Extraction: The assimilation of sensor information, such as that collected by a saliva sensor, by cloud or destination, needs to be delivered and processed in real-time for health monitoring purposes. Scalable data storage that can handle the volume of data from multiple sensors in a context that makes sense to the healthcare professional is necessary (Li et al., 2024). Conclusions: In summary, it is only when the issues discussed here are addressed and resolved that we will be able to fully exploit the enormous potential of salivary biosensor use for non-invasive, real-time in situ monitoring of health in a more effective manner for clinical care. The remarkable contribution of the research is as follows:

- Real-time Monitoring: Saliva sensing has significantly enhanced real-time health monitoring by providing a non-invasive, user-friendly, and accurate means to monitor an individual's health condition continuously. Early identification and prevention of medical conditions and illnesses lead to healthier lives overall.
- Biomarker Detection Extension: A representation of the expansion of the types of biomarkers that saliva sensing can be extended to, which goes beyond traditional blood-based biomarkers. It has enabled the measurement of numerous health assessments, including hormone levels, electrolyte levels, and infectious disease markers, to be done without a syringe and a lab visit requiring a deductible (Kammarchedu et al., 2022; Hassan et al., 2025).
- Personalized Healthcare: Saliva-based sensing can provide instantaneous feedback on an individual's health, enabling customized approaches to intervention and treatment. Personalized medicine can significantly enhance disease management and increase overall health benefits. Research results have confirmed that personalized healthcare can deliver better care at a lower cost.

The remainder of the research is organized as follows. The recent related literature is described in Chapter 2. The proposed model is presented in Chapter 3, and a comparative study is presented in Chapter 4. Lastly, Chapter 5 presents the results, while Chapter 6 explains the conclusion and scope for further work.

2 Related Words

Peddi & Ramana, 2023 proposed a scheme that exploits data streaming from commercial wearable devices to monitor personal health and wellness. With the use of AI, it can analyze data and provide personalized, intelligent guidance on healthcare management and intervention at the individual level like never before. Its purpose is to maximize general health and facilitate preventive health monitoring. (Chenani et al., 2024) Wearable electrochemical biosensors based on hydrogel. Ultra flexible hydrogel-based wearable electrochemical biosensors exhibit good biocompatibility, flexibility, and sensitivity and have the potential for real-time real-time biofluid monitoring. The limitations, such as short-term stability and low precision, as well as the materials and design developments of these sensors from the laboratory to the market, are described. Liu Y. et al. suggest that Wrist-based sensors could offer real-time, personalized surveillance of drug levels and physiology, which has the potential to optimize and personalize therapy in precision medicine. It disrupts the traditional model of drug prescription and leads to more effective and individualized treatment. (Manickam et al., 2022) have reported the emerging technologies of Artificial Intelligence (AI) and the Internet of Medical Things (IoMT) as new trends that, when integrated with biomedical systems, can contribute to the provision of efficient and precise healthcare services. If all goes well, AI can understand and process medical data, assisting in diagnoses and treatments. On the other hand, the IoMT enables the real-time collection and monitoring of patient data, allowing it to be communicated among all stakeholders to achieve better patient outcomes and improved health management. (Sharma et al., 2021) highlighted wearable biosensing systems, which are small, motion-sensing devices that can be attached to a user's body to gather data about vital signs, physical activity, and other health-related measurements. They offer an attractive, non-invasive approach to continuously monitoring personal health, providing new potential for managing and preventing diseases. (Kalasin et al., 2021) proposed Lab-on-eyeglasses as a new approach for non-invasive monitoring of kidney function through tear analysis instead of blood analysis. By utilizing machine learning algorithms, the exact prediction of serum creatinine levels can be achieved, which may be of value for early detection and intervention in kidney disease among vulnerable patients during infectious pandemics. (Oliveira et al., 2023) Very recently, Carvalho et al. "Saliva diagnosis of Zika virus infection could be estimated with high Diagnostic capacity (AUC~99%, procure higher sensitivity, leading to more accurate diagnosis on ZIKV infection, which would be based (sensitivity 100% and specificity 80%." Based on machine learning, a related study by Leite e Silva presented two new studies: Salivary Detection using a machine learning algorithm and a univariate interference algorithm (PLS-DA). These studies tested diagnostic models of Zika virus and the salivary ATR-FTIR technique for point-of-care models, predicting infection when combined (El Salhi et al., 2025). Such an approach would analyze a particular biomarker in saliva and would be both rapid and non-invasive. The development of an effective and sensitive method for detecting the Zika virus may play a crucial role in early diagnosis and intervention. (Raja et al., 2024) have reported that, due to their exceptional features of high sensitivity and biocompatibility, graphene-based sensors have been the focus of many researchers in healthcare monitoring and diagnosis. Owing to the combination of lab-on-chip devices and advanced computing capabilities, researchers have recently exploited the real-time and high-accuracy sensing capabilities of these sensors for detecting various health parameters, facilitating diagnosis and timely treatment of diseases. (Sadiq et al., 2024) have, however, discussed High-Tech Herding, in which the authors explored advanced technologies, including the Internet of Things (IoT) and Unmanned Aerial Vehicles (UAV), for monitoring and managing health issues in dairy farm systems. The system can provide real-time and dynamic assessment of the health status of animals, thereby offering improved disease detection and prevention in dairy-based livestock. (Richer et al., 2024) have proposed a machine learning-based system for detecting acute psychosocial stress through algorithms that process body postures and movements to identify signs of stress. It appears that this approach is a promising one for precise stress detection and can be adopted in many realistic scenarios as a mental health supervision and intervention system. (Subhash et al., 2021) introduced a bimodal multispectral imaging system for the acquisition of images of possibly malignant oral lesions under two light sources. These images are then analyzed via a machine learning algorithm in the cloud in "real time" to detect irregular areas. It can also aid in biopsy and provide accurate confirmation of this type of lesion, with the aim of rapid diagnosis. (Nimmagadda et al., 2023) DELVES- Epidemiology of Lyme disease in recent years, several projects (e.g., Kidney failure detection and predictive analytics for Chronic Kidney Disease (CKD)) have been developed where machine learning algorithms are used to process patient records to make predictions about (in this case) CKD associated kidney failure. Such approaches facilitate the identification of high-risk patients to target for intervention and minimize the burden of CKD on both the patient and the healthcare system. (Agrawal et al., 2022) have reported that machine-learning models are also being developed for non-invasive glucose monitoring of diabetic patients. The models utilize data from wearables and other smart healthcare devices to accurately forecast blood sugar levels, enabling individuals to manage their condition in real time. This is to maximize the treatment effect in diabetes and improve the quality of patient-centered care. (He et al., 2023) have presented Wearable technology for healthcare applications, including miniaturized point-of-care (POC) chemical sensors to detect and track target biochemical indicators in body fluids for personalized and preventive medicine. Used in combination with other techniques, such sensors have the potential to provide real-time health status and on-demand therapies, leading to an enhancement of health and personal healthcare. (Mostafa et al., 2024) have proposed a state-of-the-art (SoA) cryptographic model for real-time drone image-based face mask detection in public places and drone video surveillance, utilizing a YOLO-based deep learning model (Haval & Afzal, 2024). It utilizes a joint face-detection-and-classification neural network to predict a mask. This configuration enables quick and precise scanning of large areas of exposure, making it useful for compliance monitoring of mask-wearing restrictions. Table 1 The Comprehensive Picture: Coverage and Cuts.

Table 1: Comprehensive analysis

Author	**Year**	**Advantage**	**Limitation**
Peddi & Ramana, 2023	2023	Improves patient care and outcomes by providing real-time monitoring and analysis of personal health data collected from wearable devices.	Lack of accessibility for low-income individuals due to the use of expensive commercial wearable devices.
Haval & Afzal, 2024	2024	Continuous and non-invasive monitoring of biofluids for early detection and management of health conditions.	Limited biocompatibility of hydrogels can lead to inflammatory response or tissue damage in some individuals, limiting their use for long-term monitoring.
Liu et al., 2023	2023	Improved medication adherence and dose optimization leading to better treatment outcomes and reduced risk of adverse effects.	One limitation could be the cost of developing and implementing wearable sensor technology for widespread use.
El Salhi et al., 2025	2022	Increased accuracy and efficiency in diagnosing and treating medical conditions through predictive analysis and real-time monitoring of patient data.	Potential for AI to make errors, malfunction or fail resulting in incorrect diagnoses or treatment.
Sharma et al., 2021	2021	Continuous and real-time monitoring of physiological data can improve early detection and management of health conditions.	May not accurately capture data from certain movements or activities, leading to incomplete or inaccurate health monitoring.
Kalasin et al., 2021	2021	The advantage of using machine learning to predict serum creatinine with tear creatinine is its accuracy and efficiency in monitoring kidney health and identifying vulnerable populations during pandemics.	Inaccuracy or variability in tear creatinine levels, which may affect the accuracy of the machine learning algorithm in predicting serum creatinine levels.
Oliveira et al., 2023	2023	Non-invasive and quick method for detection of zika virus infection, providing potential for early diagnosis and treatment.	Limited sensitivity and specificity for early detection of infection, leading to potential false negative or false positive results.

Raja et al., 2024	2024	Improved sensitivity and accuracy of detecting biomarkers and diseases due to the high surface-to-volume ratio of graphene and advanced computational analysis.	The high cost of producing graphene-based sensors may limit their wide-scale implementation in healthcare systems.
Sadiq et al., 2024	2024	Improved health surveillance on dairy farms allows for early detection of diseases, preventing potential outbreaks and improving overall herd health.	The cost of implementing high-tech herding may be prohibitive for smaller dairy farms or farms in developing countries.
Richer et al., 2024	2024	Machine learning can provide accurate and objective detection of acute psychosocial stress from body posture and movements, reducing the potential for human error or bias.	Difficulty accurately identifying stress in individuals with atypical or non-uniform body movements.
Subhash et al., 2021	2021	Real-time detection and guidance for potentially malignant lesions, improving the accuracy and speed of diagnosis.	Limited availability and access to cloud-based technology and may be affected by internet connectivity issues.
Nimmagadda et al., 2023	2023	Machine learning can help detect kidney failure and predict CKD early on, increasing chances of successful treatment and management.	One limitation is that the predictive accuracy may vary depending on the quality and quantity of input data used for training the model.
Agrawal et al., 2022	2022	The ability to provide continuous and real-time glucose monitoring, reducing the need for frequent invasive blood sugar tests.	The need for continuous calibration and validation of the models for accurate and reliable glucose measurements.
He et al., 2023	2023	Improved individual health monitoring and early detection of disease, leading to more effective preventative treatments and personalized healthcare.	Limited accuracy due to variations in individual physiology and external factors such as temperature, humidity, and mobility.
Mostafa et al., 2024	2024	This model allows for accurate and efficient face mask surveillance and enforcement in large and crowded areas.	The accuracy of the model may decrease when detecting small, partially covered, or obscured faces due to limited training data of those instances.

Accuracy and Reliability: Significant technical challenges remain in saliva sensing for real-time health monitoring (21). Saliva, diet, hydration, and medications may affect the precision of the findings. Thus, it is desirable to develop sensitive and selective sensors for detecting biomarkers in saliva.

- Detection and Sensitivity The most challenging aspect of saliva-based sensors is their capability to detect and quantify the levels of a wide variety of biomarkers. There is also perhaps a range of other health conditions or diseases that will require the detection of a specific profile of biomarkers so the key to the technology is creating sensors that are sensitive enough to detect them. Achieving this high sensitivity is not a simple matter; it involves sophisticated sensor designs, signal enhancement, and careful calibration.

Outside interferences: Interference from the outside can affect saliva testing due to environmental impurities, leftover food, and other elements inside your mouth that may interfere with the reliability of the results. 54-57, the above interferences have been removed by appropriate sample preparation and sensor design, allowing for reliable measurement. When designing a sensor, it's essential to consider that saliva encompasses a spectrum.

One of them is Artificial Intelligence, and a subset of AI, namely Machine Learning, has found several applications in different domains, including healthcare. More recently, studies on saliva sensing have also been attracting interest. Besides blood, saliva is the next most readily available and informative fluid to provide external details of a person's physiological health. This data can be analyzed and interpreted by these algorithms using machine learning to uncover patterns and markers of various diseases. It would revolutionize the early detection and tracking of disease, much as physical exams, blood work, and biopsies have in the past, and would be more sensitive than today's blood tests, which measure higher levels of protein in the blood, researchers said. Additionally, this will be faster and more efficient in identifying patients with the disease profile using machine learning Capabilities In Saliva Sense, Implementing Machine Learning (Camel). With its unique use case of saliva sensing and machine learning, it has the potential to be a game changer for healthcare and research, opening doors to new diagnostics.

3 Proposed System

A. Construction Diagram

- **Capture Image Using Smartphone:**

The creation of an image with a smartphone is a multistage, intricate process that combines to provide the desired effect. These processes can be generally divided into three stages: capture, processing, and output. The smartphone's camera sensor captures light from the photographed scene, which is then processed by an image sensor implemented in the smartphone, typically using a CMOS image sensor.

One method for outlier detection is the Interquartile Range (IQR). The IQR is the difference between the first and third quartiles. The left and right limits can be expressed as follows:

$$IQR = T_3 - T_1,$$
$$C_1 = T_1 - 1.5 * IQR,$$
$$C_w = T_3 + 1.5 * IQR. \quad (1)$$

Values that are higher or lower than these isolines are outliers and should be removed. Once discovered and addressed, these outliers can be excluded from the dataset.

As all outliers' have been removed in the last stage and our features are mostly normally distributed, we'll standardize our dataset using the method StandardScalar. Here is the conversion formula:

$$m^* = \frac{m-\mu}{\sigma} \quad (2)$$

$$\underset{u}{Min} \sum_{j=1}^{Y} \left(u^Q m_j - n_j\right)^2 + \lambda u_1 \quad (3)$$

To evaluate the accuracy of the model's predictions, we use Binary Crossentropy as the loss function.

$$G_e(t) = \frac{1}{Y} \sum_{j=1}^{Y} n_j \, log\left(e(n_j)\right) + \left(1 - n_j\right) log\left(1 - e(n_j)\right) \quad (4)$$

Binary cross-entropy is often used for binary classification. Loss using the Binary Cross-entropy is calculated using the following equation.

$$Re\,L\,u(m) = max(0, m)$$

$$Sigmoid(m) = \frac{1}{1+p^{-m}} \tag{5}$$

Additionally, with Sigmoid, it is easier to limit the output compared to ReLU. Below are the Sigmoid and ReLU functions. We can interpret the output of the Sigmoid as the probability that the input falls into the "yes" category. Therefore, we label the data by one-hot encoding.

This sensor consists of millions of small, photosensitive cells, or pixels, that transform light into electrical signals. Every pixel can measure the intensity of the light that strikes it, which controls the color and brightness of that point. The phone utilizes methods such as auto-focusing and optical image stabilization to produce sharp and focused images.

- **Pre-processing:**

Preprocessing is the most crucial phase in data analysis, focusing on the basic steps involved before the data becomes available to the study. This is necessary to be able to bring the data into a more useful and higher quality (for the types of analysis) format that such analytical techniques require as input. Data Cleaning: Data Preprocessing commences with data cleaning, where missing values, duplicate records, and anomalies are detected and addressed. What are missing values? The missing values for a particular observation may be due to a crazy number of errors caused by human factors, data sensor errors from certain sensors, and so on. They can be everywhere, and this makes the threat model vulnerable to empty values if you don't take care of cleaning them. The construction diagram is shown in the following Figure 1.

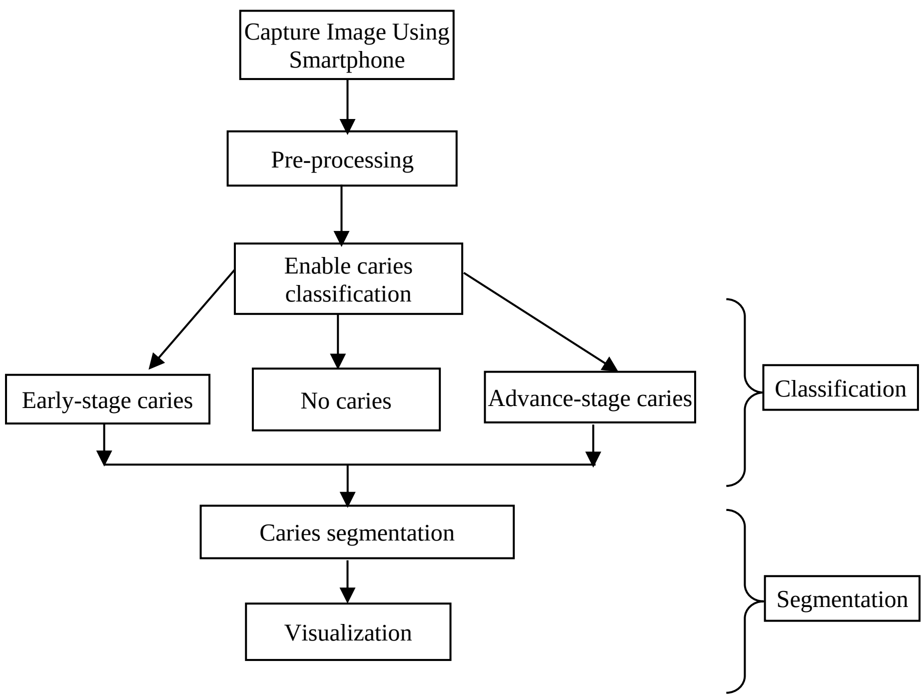

Figure 1: Construction diagram

These missing data can affect the results of the analysis and must be treated properly. This can be done using techniques like imputation, where missing values are replaced with estimated values inferred from the rest of the data, or you can remove the observation if doing so will not significantly affect the analysis result.

➢ Enable Caries Classification:

"Enable caries classification" is a feature or plugin for dental imaging software that enables the automatic detection and classification of caries (basically cavities). The system utilizes advanced algorithms and artificial intelligence (AI) to analyze digital images of the patient's teeth, resulting in an accurate and objective detection of caries. The method for ranking caries includes the following steps: performing a first procedure and taking high-resolution, high-bit-depth digital images of the patient's teeth. Intraoral pictures, X-rays, or other imaging may offer it. You then input the images into a software program, and it assigns a score; that's it. The program performs various pre-processing procedures on the images (e.g., noise reduction, contrast enhancement, image calibration) to enhance the image quality when used for caries detection.

➢ Early-stage Caries:

Introduction Tooth decay, or dental caries, is a prevalent dental disease in which the outer covering of the teeth, enamel, is damaged by acids made by bacteria in the mouth. This damage may lead to the formation of tiny cavities or pockets in the teeth that can advance and cause more damage as they spread. The progression of caries at the initial stage is a slow development, beginning with the accumulation of plaque on the tooth surface. Plaque is a sticky film that accumulates throughout the day on the surface of the teeth, consisting of bacteria, food debris, and saliva.

As for Xavier, initialization is divided into two while preserving the variance in such a way that half of the neurons in a layer are active. All neurons in all layers are active. He initialization the Xavier one, and

$$u_j \sim W\left(-\sqrt{\frac{6}{y_j+y_{j+1}}}, \sqrt{\frac{6}{y_j+y_{j+1}}}\right) \tag{6}$$

$$u_j \sim \frac{\left[W\left(-\sqrt{\frac{6}{y_j+y_{j+1}}}, \sqrt{\frac{6}{y_j+y_{j+1}}}\right)\right]}{2} \tag{7}$$

The G generation population's evolution is depicted using D, x G. Each person consists of the following characteristics. D, which has the following formula for expression,

$$m_j^H = \{m_{j,1}^H, \ldots\ldots, m_{j,F}^H\}, j \in \{1,2,\ldots., NP\} \tag{8}$$

For the mutation, DE chooses a random perturbation. The relationship it describes demonstrates that,

$$z_j^H = m_{l_1}^H + D.\left(m_{l_2}^H - m_{l_3}^H\right), l_1, l_2, l_3 \in \{1,2,\ldots., NP\} \tag{9}$$

The bacteria in plaque feed on sugars from our food, producing acids as a by-product. These acids gradually dissolve the minerals in the enamel, weakening and softening it. As the enamel becomes demineralized, it becomes more susceptible to damage. The early stages of caries, also called the demineralization stage, involve the loss of minerals such as calcium and phosphate from the enamel.

➢ Advance-stage Caries:

Severe decay, also known as advanced or deep decay, is a condition in which bacteria in a person's mouth infect the hard outer layer, or enamel, of the teeth and progress over time. Through a process called demineralization, that acid erodes the minerals that form the tooth, but only if it sits on the tooth for more than a moment or two. If it continues to grow downward into the tooth, it may cause permanent damage and necessitate a tooth extraction. This advancement of advanced-stage caries is classified into three stages, ranging from early to advanced ones. Decay is limited to the enamel and can be arrested if detected in time through good oral hygiene and the use of fluoride.

And in this way, hapless mutations are... The dimension D criteria are determined using a cutoff. However, over time, decay can sometimes advance into the softer layer beneath the enamel, known as dentin.

$$z_{j,i}^{H} = \begin{cases} z_{j,i}^{H}, if rand_i \leq CRor i = i_{rand}, \\ m_{j,i}^{H}, otherwise, i = 1, \ldots\ldots, F, \end{cases} \tag{10}$$

This is called the moderate phase, and at that stage, decay can no longer be reversed. The bacteria eat away at the dentin, and the caries can progress into the intermediate or advanced stages of the pulp as they move further into the tooth and reach the nerves and blood vessels.

B. Functional Working Model

➢ Data Normalization:

Normalization is a data modeling process in which data are organized in a database to minimize redundancy and dependency. It is the phase where data is converted and organized into a format or structure that can be used to manage, analyze, and query the data. The essence of normalizing is to store data consistently and correctly in a way that eliminates redundancies, duplicate data, and anomalies.

$$z_{l}^{H+1} = \begin{cases} z_{j}^{H}, if g\left(w_{j}^{H} \leq g\left(m_{j}^{H}\right)\right), \\ \quad m_{j}^{H}, otherwise, \end{cases} \tag{11}$$

This study uses thresholds from the action potential range as its methodology. The following formula can be used to determine the threshold value:

$$\begin{cases} \sigma_y = median\left\{\frac{|m|}{0.6745}\right., \\ Threshold = 3.5\sigma, \end{cases} \tag{12}$$

One crucial component in determining the presence of dynamic impediments with torsions is the accurate alignment of torsions. Like every network, this one requires training. The goal of this tutorial is to identify a mapping similar to the one in the following equation.,

$$g(z) = \sum_{j}^{y} u_j \varphi\left(\left|\left|z - B_j\right|\right|\right) \tag{13}$$

One of the critical concepts of normalization is to break down data into multiple tables rather than storing all the information in a single table. This is known as database normalization, and it helps eliminate data redundancy. Redundant data consumes more storage space, resulting in consistency and accuracy issues. "Dividing" the data and linking the data in several tables would not create these duplications and would not allow those inconsistencies between the data.

➢ Data Cleaning:

Data Preprocessing is an important step in data analysis that involves identifying and removing incomplete, incorrect, inaccurate, or irrelevant data elements from a dataset. This is also referred to as data cleaning, scrubbing, or preprocessing. "This is important because if the data being analyzed is accurate, consistent and complete, then this will lead to more valuable results… it's more useful as we have increased confidence in the recommendations and trends produced by big data." Data Cleaning

Step 1: Identify and Handle Missing Values. Remember to handle missing values before moving to the next steps. A functional block diagram is shown in Figure 2 below.

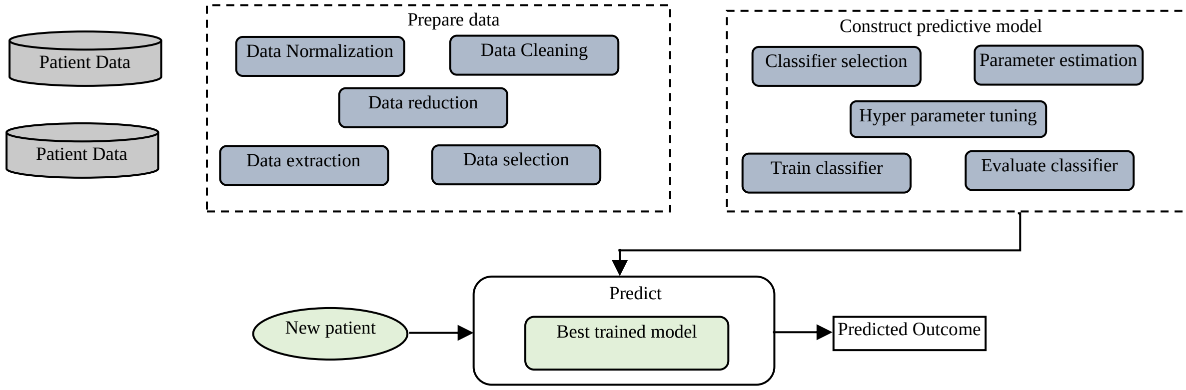

Figure 2: Functional block diagram

To do this, one must understand the nature of the missing values and determine how to address them. It could involve deleting the N/A values, filling them in with the average or median of the column, or applying complex statistical methods such as regression or interpolation. Now, it's time to confirm and correct bad data.

- **Data Reduction:**

Data reduction is a process in which a large and complex dataset is transformed into one that is manageable while still retaining important information. Eliminating redundant, noisy, or irrelevant information reduces memory and computational costs, thereby improving data management and analysis. This is particularly important for finance, healthcare, and research, where massive amounts of data are processed daily. Data preprocessing begins with raw data (text, numbers, images, videos). Since then, data (before any processing) can be considered raw and unstructured, often containing noise or irrelevant information; this must be removed to obtain meaningful insights. For each input training vector or P value of signal data, the overall network error is given by. Training is halted if the error P becomes less than the threshold error. This value is initialized to a manual value at the start of the work. The latter will be a list that illustrates the current position of the torsion layer within the convolutional neural network (CNN), with or without a coronary artery.

$$\phi(z) = exp\left(\frac{-z^2}{2\sigma^2}\right) \tag{14}$$

$$p_j = q_j - n_j = q_j \sum_{i-1}^{Y} u_i \varphi\left(\left|\left|z_j - B_i\right|\right|\right) \tag{15}$$

The following equation defines the percentage as an array: Data reduction in BT instruments can be divided into three steps: cleaning, data verification, and data completeness checking. Any missing or incorrect data is then corrected or deleted to provide a more accurate dataset.

$$Convolve = \left[m_1, m_2, \ldots., m_{Y_{var}}[]\right] \tag{16}$$

$$profit = d_e(Convolve) = d_e\left(m_1, m_2, \ldots.., m_{Y_{var}}()\right) \tag{17}$$

$$i\left(m^{(j)}, \ldots\ldots., m^{(y)}, \theta^{(1)}, \ldots.., \theta^{(y)}\right) = \frac{1}{2}\sum_{(j,i):l(j,i)-1}\left(\left(\theta^{(i)}\right)^{Q} m^{(j)} - n^{(j,i)}\right)^2 + \frac{\lambda}{2}\sum_{j=1}^{y_x}\sum_{s=1}^{y}\left(m_s^{(j)}\right)^2 + \frac{\lambda}{2}\sum_{j=1}^{y_w}\sum_{s=1}^{y}\left(\theta_s^{(i)}\right)^2 \tag{18}$$

Data Integration: Once you have performed some data crunching, it will be time to integrate it, that is, to combine data from multiple sources, such as databases, spreadsheets, and web applications.

- **Classifier Selection:**

The phenomenon is that people often select algorithms from the machine learning toolbox, and the task of choosing them is surprisingly required. It is sometimes referred to as "model selection" or "algorithm selection" and is necessary to achieve improved predictive accuracy and performance. The First Step to Choosing a Classifier Step #1: Model Selection: Gather Information to Understand the Problem and the Data AvailabIe (This means looking to see how many different types of features you have in your dataset, the size of the dataset and the type of outcome/target variable that you'd you like to predict.) This one will remove part of a large number of algorithms that can be used for this problem. Knowing this, you can concentrate on trying out various classifiers. To do so, the learner trains and cross-validates multiple classifiers on the input datasets with varying hyperparameters and performance criteria. The traditional classifiers include decision trees, support vector machines (SVMs), k-nearest neighbors (KNN) models, and neural networks, among others.

- **Best Trained Model:**

Best-Training Model: A best-training model is the combination of a trained model and an algorithm that learns by using a specific trained model to predict new data, often tailored for a specified dataset. This pipeline is a chain of actions that contains training and parameter tuning. One of the first decisions made in model training is which model to use. Here, it includes the type of neural network, depth, and the number of neurons per layer. It is essential to design the model's structure according to the dataset itself and the specific problem at hand.

To detect coronary heart disease, the above function may be minimized as much as possible.

$$\min_{\substack{m^{(1)},\ldots,m^{(y_x)} \\ \theta^{(q)},\ldots,\theta^{(y_x)}}} i\left(m^{(1)},\ldots,m^{(y)},\theta^{(1)},\ldots,\theta^{(y)}\right) \tag{19}$$

$$Max_{ConnectedLayer} = \alpha \times \frac{numberofcurrentlayers}{totalnumberoflayers} \times \left(Var_{high} - Var_{low}\right) \tag{20}$$

Once we have defined our model architecture, we must create a method for initializing the weights of our network. These weights are the magic numbers that determine exactly how the model transforms the input into its predictions. This is achieved by training the model while it learns weights on the available data, where the training data influences the model to be capable of identifying any patterns and relationships that might exist in the data.

C. Operating Principle

- **Attention Layer:**

The attention layer is an indispensable component in many deep learning models, in particular those for NLP applications (e.g., machine translation and text summarization). The goal is to enable the model to attend to different input parts at various levels of processing. The Attention layer serves as a model that focuses on the most important or necessary part of the information for specific tasks.

$$M_j = \ll M_j^1, M_j^2, M_j^3, \ldots\ldots, M_j^y \gg \tag{21}$$

A feature vector is X i. One of the components j of the feature vector i is %e X ji.

$$g = \alpha \frac{1}{y} \sum_{j=1}^{y} \left|\bar{N}_j - N_j\right| + \beta . \frac{D}{A} \tag{22}$$

Each included feature has a value of zero or one to show whether the feature selection has) and has been selected. In tasks with long data sequences, it is useful when a model needs to remember and focus on certain past information. In essence, the attention layer assigns weights to various positions in the input sequences according to their importance. These weights are computed from dot products, cosine similarities, or learned parameters. The calculated weights are then used to calculate the weighted sum of the input and forwarded to the next layer of the model.

- **Context Vector:**

The context vector is a crucial component of natural language processing (NLP) and machine learning algorithms, particularly in tasks involved with understanding the meaning behind words and sentences. It is a vector representing the context or surrounding information of a word or sentence in a given text. This context can include the words before and after the target word, as well as other linguistic features such as part-of-speech tags and sentence structure. The operational flow diagram is shown in the following Figure 3

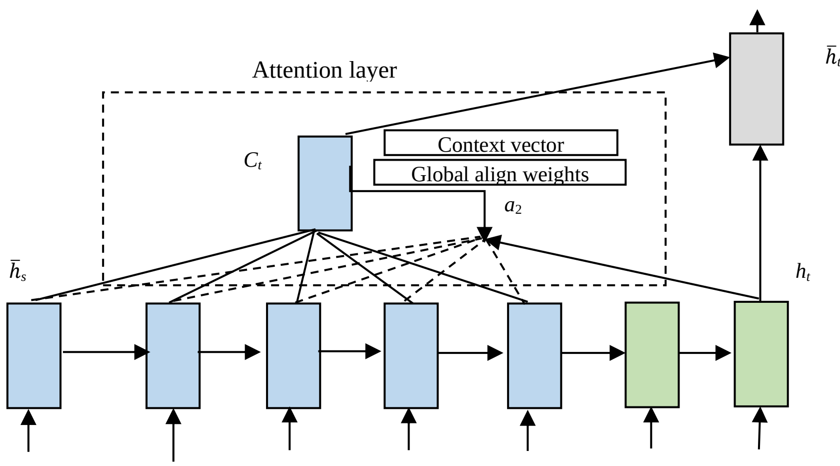

Figure 3: Operational flow diagram

The primary goal of a context vector is to encode the semantic relationships and connections between words within a given text. This is achieved by applying advanced mathematical and statistical models to capture word co-occurrence patterns in a massive text corpus. The resulting vector represents a high-dimensional context for a given word.

- **Global Align Weights:**

"Global align weights" is an operation used in sequence alignment algorithms to find the best possible alignment between two sequences of characters, such as DNA or amino acid sequences. It is a dynamic programming approach that aims to find the optimal alignment by assigning weights to each possible alignment between the two sequences.

Every iteration displays the ideal feature vector. It is used to add random motions to feature vector updates.

$$M(q+1) = \begin{cases} M_{rand}(q) - l_1 |M_{rand}(q) - 2l_2 . M(q)|, rand \geq 0.5, \\ \left(M_{rabbit}(q) - M_X(q)\right) - l_3\left(LB + l_4(UB - LB)\right) rand < 0.5 \end{cases} \tag{23}$$

Consequently, the subsequent equation is created:

$$M(q+1)=\begin{cases}M_{rand}(q)-l_1|M_{rand}(q)-2l_2.M(q)|, rand \geq 0.5,\\ \left(M_{rabbit}(q)-M_X(q)\right)-l_3.l_4 rand < 0.5\end{cases} \tag{24}$$

$$M(q+1)=\left(M_{rabbit}(q)-M(q)\right)-P|I.M_{rabbit}(q)-M(q)| \tag{25}$$

$$M(q+1)=M_{rabbit}(q)-P|M_{rabbit}(q)-M(q)| \tag{26}$$

$$M(q+1)=M_{rabbit}(q)-P|I.M_{rabbit}(q)-M_x(q)| \tag{27}$$

Every iteration, the feature vectors are updated with the goal of diagnosing the condition through the deployment of these associations. The best feature vector is used in the last iteration to reduce disease-related diagnostic mistakes.

$$U_1=\frac{(1\times 2\times \pi)}{360} \tag{28}$$

$$U_2=\frac{13\times 2\times \pi}{360} \tag{29}$$

The frequency at which the input signal is received. The filtered signal is displayed.

Equation (23) calculates signal averaging, and in the convolutional neural network, finding standard deviation during training and testing of data is calculated in

$$Fi=\frac{1}{X}\sum_{q=1}^{x} Qq$$

$$var\ i\ ance=\frac{1}{X}\sum_{q=1}^{x} Qq \tag{30}$$

$$Cov=AA^Q \tag{31}$$

where the matrices are A= Variance1, Variance2,..., Variancen, and Cov=N2∗ N2. As a matrix, A= N2∗ M, Covis has a large value. Special values of Cov can now be derived by applying the equation that follows:

$$T_j=AZ_j \tag{32}$$

The first step in the global align weights operation is to create a scoring matrix, also known as a substitution matrix. This matrix contains values for each possible substitution between the characters in the two sequences, where higher values indicate a better match. This scoring matrix can be generated using various techniques, such as the BLOSUM or PAM methods.

4 Result and Discussion

The proposed model, HMM-SM - Hidden Markov Models for Saliva Monitoring, has been compared with existing models: CNN-SM - Convolutional Neural Networks for Saliva Monitoring, SVM-ESM - Support Vector Machines for Ensemble Saliva Monitoring, and ETLS - Evolutionary Tree-Based Learning for Saliva Monitoring.

4.1. Accuracy

Accuracy is one of the key indicators used for evaluating machine learning performance in the context of saliva sensing for real-time health monitoring. This is the method's capacity for accurately identifying and measuring a variety of health marker compounds in saliva. Accurate measurements are critical for diagnosing and monitoring health conditions, but if those readings are incorrect, the wrong treatment can be administered, or the diagnosis can be completely inaccurate. Table 2 Comparison of Accuracy of Proposed Model with Existing Models. Figure 4 Illustration of Accuracy Calculation

Table 2: Comparison of accuracy (in %)

No. of Inputs	CNN-SM	SVM-ESM	ETLS	HMM-SM
100	55.36	40.79	34.82	60.55
200	53.87	38.82	32.40	58.35
300	53.07	37.69	31.99	57.55
400	50.74	36.48	30.39	56.88
500	49.73	36.11	28.07	55.45

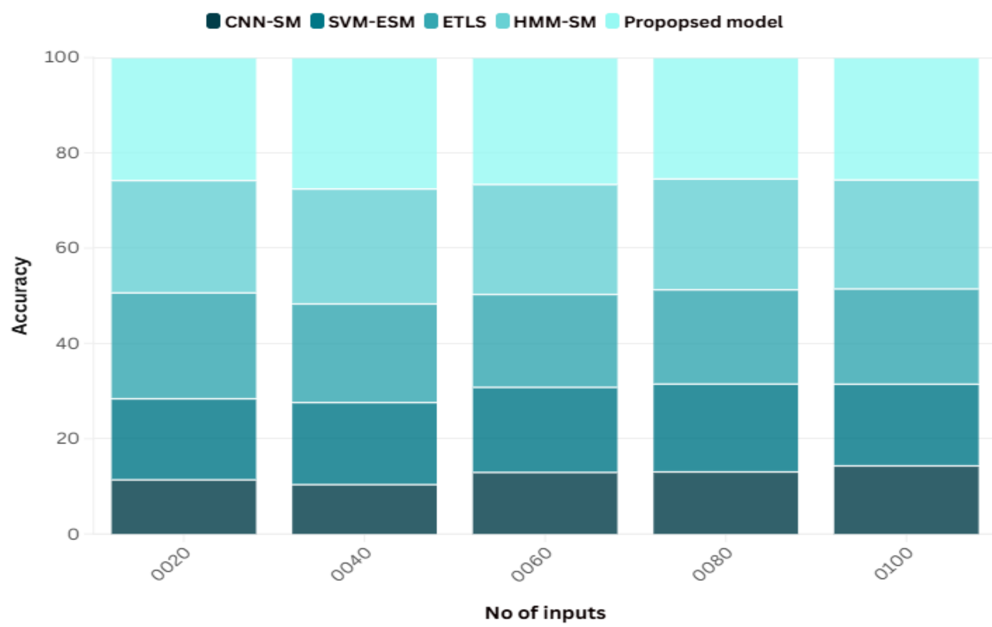

Figure 4: computation of accuracy

4.2. Sensitivity

Another technical performance metric is sensitivity, which describes the technology's ability to detect changes in low amounts of biomarkers in saliva. A reactive AI system would be able to recognize very small changes in levels of biomarkers indicative of early-stage health conditions. Table 3. The sensitivity comparison between the previous and new models is presented in Figure 5 and 6. Sensitivity Calculation 4.3.

Table 3: Comparison of sensitivity (in %)

No. of Inputs	**CNN-SM**	**SVM-ESM**	**ETLS**	**HMM-SM**
100	61.36	45.79	41.82	65.55
200	59.87	43.82	39.40	63.35
300	59.07	42.69	38.99	62.55
400	56.74	41.48	37.39	61.88
500	55.73	41.11	35.07	60.45

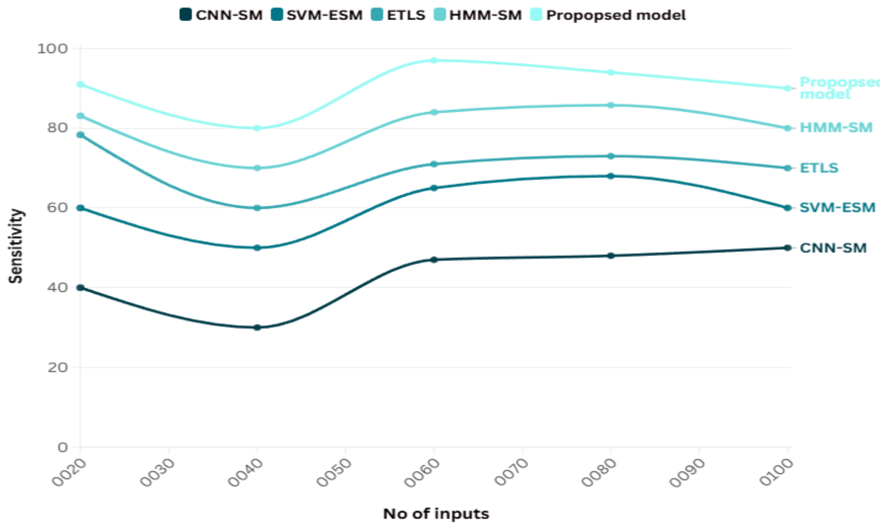

Figure 5: Computation of sensitivity

4.3. Speed

To enable real-time health monitoring, the fast and timely detection of potential anomalies in saliva is imperative. Thus, the computational efficiency of the machine learning system plays an important role. It should be able to work through spit samples as quickly as possible while also providing rapid results. A sluggish system can hinder the timeliness of diagnosing and treating health conditions — with serious consequences. Table 4 presents a comparison of speed between the current and proposed techniques. Figure 6 Speed Calculation.

Table 4: Comparison of speed (in %)

No. of Inputs	CNN-SM	SVM-ESM	ETLS	HMM-SM
100	65.36	52.79	47.82	71.55
200	63.87	50.82	45.40	69.35
300	63.07	49.69	44.99	68.55
400	60.74	48.48	43.39	67.88
500	59.73	48.11	41.07	66.45

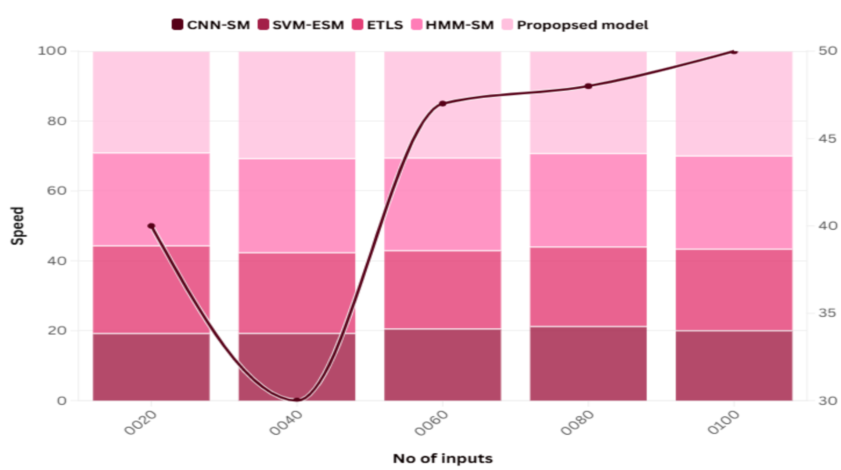

Figure 6: Computation of speed

4.4. Adaptability

The human body is one of the most complex and dynamic biological entities, making it challenging to apply health monitoring technology universally. The power of machine learning is invoked; an appropriate performance metric hereabouts would be how well such an approach can adapt and alter its algorithms in response to the unique interindividual variations in salivary composition and shifting levels of biomarkers due to lifestyle influences, namely, perhaps diet, medications, or other variations in daily activities (such as passive and active smoking). A flexible machine learning (ML) algorithm, which facilitates personalized and precise individual monitoring, may contribute to better health outcomes. Table 5 Adaptability comparison between original and new models is depicted in Figure 7 Display of Calculation of Speed.

Table 5: Comparison of adaptability (in %)

No. of Inputs	CNN-SM	SVM-ESM	ETLS	HMM-SM
100	69.36	57.79	53.82	77.55
200	67.87	55.82	51.40	75.35
300	67.07	54.69	50.99	74.55
400	64.74	53.48	49.39	73.88
500	63.73	53.11	47.07	72.45

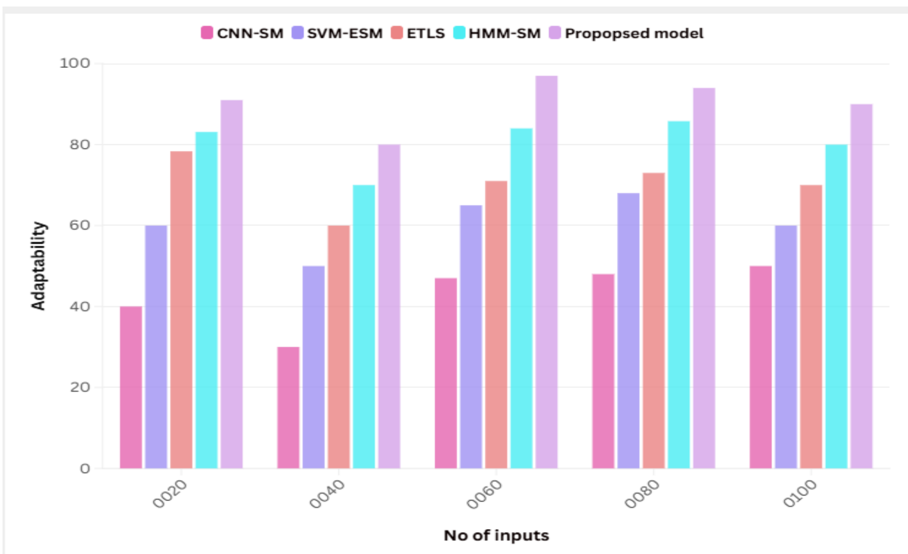

Figure 7: Computation of speed

5 Conclusion

Due to recent advancements and the increasing complexity of problems solved by machine learning, the use of machine learning has also seen rapid growth in healthcare, as well as in many other domains. One application of saliva sensing that has seen uptake is for instant health monitoring, an area where machine learning has started to make an impact. It has proven to be highly efficient in disseminating accurate health information to the public with great conciseness, thus serving as a favorable means of prevention and control. With the aid of machine learning algorithms and data-driven methods, a person's salivary constituents can now be analyzed by machine learning to assess their health status. They traipsed around the industrialized country, teasing and testing, taking samples: the breath that hung in a tube, spikes of contact in a turban worn all day … The data followed the group and its activities — hundreds of secondary outcomes — including readings for signs of disease or changes in health. If monitoring these biomarkers with micrometer resolution in real-time field tests becomes routine, this would mean that an individual's health status could be tracked daily before issues arise (Horgus 2017). In contrast, the strong points of ML in saliva-sensing, unlike conventional detection methods, are that it is a non-invasive, cost-effective, cost-effective, and portable detection method. It can even complicate health care.

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Authors Biography

Amit Sharma is a Professor in the School of Computer Applications at Lovely Professional University, Punjab. His research interests include software engineering, data analytics, and information systems. He has published numerous papers in reputed journals and actively mentors students in advanced computing projects and research.

Beemkumar Nagappan is a Professor in the Department of Mechanical Engineering at JAIN (Deemed-to-be University), Bangalore. His research areas include thermal systems, fluid mechanics, and mechanical design optimization. He has published extensively and is actively engaged in mentoring students, leading research projects, and fostering innovation in engineering education.

Nipun Setia is associated with the Centre of Research Impact and Outcome at Chitkara University, Punjab. His research expertise includes institutional research evaluation, academic analytics, and innovation management. He works on projects aimed at enhancing research quality, promoting interdisciplinary collaboration, and supporting data-driven decision-making in higher education.

Yuvraj Parmar is affiliated with the Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh. His research focuses on academic strategy, research management, and institutional development. He contributes to projects that improve research quality, foster innovation, and support interdisciplinary collaboration within higher education.

Vijay Jagdish Upadhye is an Associate Professor in the Department of Microbiology at Parul University, Gujarat. His research interests include microbiology, biotechnology, and applied microbial studies. He actively mentors students, leads research initiatives, and contributes to publications advancing knowledge in microbiological sciences.

Pavan Chaudhary is an Assistant Professor at the Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh. His research focuses on computer science, software systems, and artificial intelligence. He is actively involved in teaching, mentoring students, and conducting research projects to advance innovative solutions in computing and engineering education.