Integrated Machine Learning Framework for Automated Vehicle Monitoring System for CVD Patients

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Article Info
Page Number: 4547 - 4557
Publication Issue:
Vol 71 No. 4 (2022)

Article History
***Article Received**: 25 March 2022*
***Revised**: 30 April 2022*
***Accepted**: 15 June 2022*
***Publication**: 19 August 2022*

Abstract
In this paper, we design an Integrated Machine learning framework for Automated Vehicle Monitoring for CVD Patients. The study uses a machine learning algorithm to detect the heart rate and pulses of the CVD Patients who drive the vehicles. The simulation is conducted to check if the trained machine learning classifier classifies the patient's heart rate in effective manner. The results of simulation shows that the proposed method has higher accuracy than other methods.
Keywords: Machine learning, Vehicle Monitoring, Alert System, Cardiac Patients

1. Introduction

In recent decades, it is concerning that there has been a general increase trend in the number of persons who have been murdered as a result of traffic accidents all around the world. This tendency has been occurring all over the world. When a motorist is suffering from an illness or injury, the likelihood that they will either cause an accident or be involved in one is greatly increased. Because of this, anyone who is in the automobile at the time of the accident or who is close stands the danger of receiving severe injuries or even dying as a result of the incident [1].

It is possible for a person to be involved in a car crash if they have a medical condition that hinders their ability to drive safely, whether it be their physical or mental capacities, their alertness, or their ability to make good decisions. Seizures, strokes, heart attacks, impaired vision, and other medical disorders such as Alzheimer disease, Parkinson disease, and dementia are all examples of circumstances that enhance the probability of being involved in an accident [2]. When drivers are preoccupied with thoughts or activities other than driving, not only do they put themselves and their passengers in danger, but they also put everyone else who is on the road in danger.

Although estimates of the percentage of automotive accidents caused by acute medical illness varied from less than 0.1% to 3% across different studies [3, 4], this is nonetheless a significant source of morbidity and mortality in the United States. A medical condition was found to be the primary cause of 13% of the casualty incidents that were investigated in the study of 298 road accidents that took place in the metropolitan area of Adelaide, Australia, in Australia [6]. A medical condition was also found to be the primary cause of 23% of all hospital admissions and fatal crash outcomes. The study was conducted in Australia. Because of significant health issues, 98 of a total sample size of 844 Japanese cab drivers were either directly involved in an accident or came perilously close to being directly involved in an accident [7].

A coronary attack causes the death of a portion of the muscle that makes up the heart and can on occasion be fatal. A heart attack is also known as an infarction. Heart attack has the potential to be fatal, many lives can be spared and significant consequences can be avoided if the early warning signals are detected and reported to medical specialists in a timely manner. Even though a heart attack has the potential to be fatal, many lives can be spared and significant consequences can be avoided. There is an immediate requirement for a transportable and wearable monitoring system that is able to keep a constant lookout for any early signs of this particular medical condition. This system would also need to be able to alert the patient (the driver) and medical caregivers with the location of the vehicle, which would help to limit the number of automotive crashes that could have been caused by the driver having a heart attack while they were behind the wheel. In the event that a driver starts to lose consciousness while operating a motor vehicle, they will be able to pull over to a safe location in plenty of time for emergency personnel to arrive and begin administering life-saving treatments in the event that they do lose consciousness.

The recording of electrocardiogram (ECG) signals in patients who are staying in the hospital for an extended period of time is a laborious and time-consuming process using the ambulatory ECG monitoring devices that are currently in use. Additionally, in order for the information gleaned from these recordings to be processed for diagnostic functions to be sent to qualified professionals. This makes it possible for the device to monitor heart attacks in a manner that is more accurate than human monitoring. This will be of great assistance to motorists because it has the potential to save lives and prevent accidents from occurring.

In this paper, we develop an integrated Machine learning framework for Automated Vehicle Monitoring for CVD Patients. The author of the article uses machine learning to discover patients who are receiving treatment around the clock and are wearing technology that can measure their state or the number of interactions they have while the author is driving.

2. Related works

Balakrishnand et al. [7] created and constructed a system that was capable of utilizing ML algorithms to record, store, and evaluate cardiac sounds at various periods. This solution was implemented as a component of a larger integrated system.

Deperlioglu et al. [8] explained why a secure procedure needed to be incorporated into the model. This is due to the fact that the model is dependent on the Internet. In order to provide a diagnosis, the proposed model that was built by the authors makes use of the architecture of a digital stethoscope, interacting with a server that is located in the cloud through the usage of Bluetooth beacons and a convolutional neural network (CNN). The scientists partitioned the method into groups so that it could be used in a medical facility like a hospital or clinic without the need for more intricate hybrid models.

Aileni et al. [9] described a method for acquiring biological data through the use of flexible and wearable sensors in the course of their work in the intensive care unit. Their goal was to monitor the patient respiration using this method. The signal was transferred from the

Arduino to the laptop by means of Bluetooth so that it could be processed and analyzed by MatLab, which was operating on the computer, as well as an Android device.

Ukil et al. [10] suggests that the utilization of remote and automated management could result in major benefits for healthcare organizations. By providing assistance with diagnostic tests, the Internet of Things (IoT) and machine learning have the potential to reduce the amount of time that is spent on providing care to patients.

Doshi et al. [11] use remote identification of cardiac illness. The development of portable computer technology paved the way for the establishment of this brand-new industry. Both a diagnostic prototype for cardiovascular illness and a comprehensive analysis of remote diagnostic systems were put through their paces by the authors. It has been suggested that the prototype, which is easy to manufacture and does not cost too much, be utilized for remote patient diagnosis in remote rural or inaccessible places.

Evaluation of a newborn heart with PCG is described as a very difficult endeavor by Amiri et al. [12], who state that this is the case. The difficulty that is involved with determining physiological parameters from the signal that was collected from infants is one reason why this argument should be supported and why it is deserving of support. In the study, a classification scheme was applied, and its purpose was to differentiate between normal and pathological cardiac sounds.

Congenital heart disorders (CCDs), which are caused by an abnormality in the heart, are responsible for three percent of all cases of child death, according to a study that was carried out by Gómez-Quintana et al. [13]. These CCDs affect approximately one percent of infants and are responsible for three percent of all cases of infant mortality. A screening for cardiovascular disease using ultrasound is often performed on a pregnant woman somewhere between the 12th and 16th week of her pregnancy. Using the XGBoost method for machine learning, the authors sought to accomplish their objective of developing a tool with the potential to be of assistance in the clinical decision-making process. The researchers wanted to find out what they could learn from looking at the model, so they compared its accuracy to that of a seasoned neonatologist who was working with the same group of infants.

According to Chorba et al. [14], a computational technique aids in disease diagnosis through auscultation. This was done due to the fact that different medical experts have different levels of interpretative aptitude when it comes to recognizing the presence of abnormal features during cardiac auscultation. The researchers suggested applying deep learning strategies within the framework of a convolutional neural network (CNN) architecture, with the final layer employing a softmax function to normalize the probability distribution. This would be done in order to detect the conditions. This was done in order to increase the number of successful detections. In this particular instance, the instructional purposes that motivated the utilization of the publicly accessible dataset that is made available through PhysioNet.

According to Tiwari et al. [15], the pressure in the arteries is caused by the mechanical movement of the heart that takes place during the cardiac cycle. PCG is a symbol that can be used to symbolize this pressure. The authors were interested in PCG for a few distinct reasons: first, because it is a non-invasive technique, it is relatively inexpensive; second, it is simple to adapt for remote use by recording signals using a smartphone. Both of these factors contributed to the author interest in PCG. They constructed the framework for a network that was capable of measuring and identifying different heart rates in order to accomplish this objective. Both convolutional neural networks and Q transformations were utilized to create this structure.

3. Proposed Method

A intelligent sensor-based heart attack detection has components of the prototype system in Figure 1. These two subsystems are able to connect with one another through the utilization of Bluetooth low energy (BLE) technology, which enables the transport of data without the usage of wires. The sensor subsystem records the electrical activity that takes place in the chest by making use of the dry ECG electrodes. This helps to ensure accurate results. Raw signals are continuously transmitted from the body of the patient to the Bluetooth. The detection is also continuously updated with the signals that are received from the Bluetooth interface. In the final approach, the raw readings are continuously monitored and evaluated in order to search for indications of a potential heart attack [16-20].

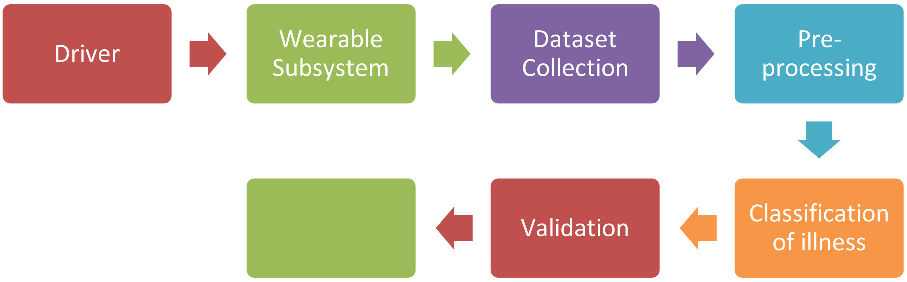

Figure 1: Monitoring of CVD Patients

The electrocardiogram is acquired in real time from the wearable component, which then amplifies, filters, and digitizes the signal before sending it over wireless transmission. This component is fastened to the chest harness that the driver must wear when operating the vehicle. This consists of a reference electrode, two differential electrodes, an analog front end (AFE), and microcontroller that has a built-in BLE module. The raw data is gathered by the dry electrodes, and after that, it is sent to the AFE to be amplified and filtered. After that, the data is converted into digital form and sent to the component of the system that is responsible for decision-making.

Drivers use chest belts that have dry electrodes sewed into them. These electrodes are more compact and may be reused. Cognionics, Inc. is responsible for their production as electrodes. In order to prevent baseline drift and saturation while maintaining a high signal-to-noise ratio (SNR). The AD8232 AFE from analog devices is able to extract, amplify (with a gain of 60 dB), and filter (with a bandwidth of 0.48–41 Hz) the signal from the electrocardiogram, even when there is noise present. The bandwidth of this filter ranges from 0.48–41 Hz (ECG) [21-23].

The module consists of a right-leg drive, an adjustable low pass filter (LPF) with three poles, an adjustable high pass filter (HPF) with two poles, and a lead-off detector. A right-leg drive that is built within the module is another feature that it possesses (RLD). Electrocardiogram signals are filtered using a Wien bridge notch filter with a center frequency of 50 Hz. This frequency is chosen since it is the most common. Following the signal digitization by the RFduino as it emerges from the notch filter, it is transmitted to the infrastructure that is responsible for making decisions.

Decision-Making System

The ability of the SIM 908 module to send and receive SMS messages, make and take phone calls, and acquire GPS data was initially tested on the command line interface. Other capabilities of the SIM 908 module included the ability to make and receive phone calls. In addition to such tests, we also tried making and taking phone calls. Using the arduPi package that was developed as part of a kitchen hack, a multi-threaded Python program was created for the RPi3 to trigger an SMS text message whenever an irregularity was identified in the ECG tracing.

This program was designed to monitor the ECG tracing and alert the user whenever an irregularity was detected. This application was developed to keep an eye on the electrocardiogram (ECG) and send a notification to the user whenever any abnormalities were found. Tests were used to evaluate the functionality of the warning system, which consists of both a local auditory alarm (a buzzer) for the driver as well as a GSM call to the pre-defined number. The functionality of the warning system was reviewed.

Machine Learning Monitoring

The study uses a feed-forward ANN because it has a solid track record. According to the findings of our research, ANNs perform significantly better than other methods when it comes to extrapolating and generalizing data.

One type of neural network is known as a feedforward network, and it is distinguished by the presence of an exhaustive connection graph. A radial basis function-based feedforward network is an example of the type of network known as a feedforward network (RBF). They are a type of generic function approximator that, when combined with adequate computing power and expertise, have the ability to construct approximations of a broad variety of functions that are arbitrarily close to the true value of the function in question.

The information that is contained in the first layer of an RBF NN is transformed in a manner that is non-linear in the second layer, which is also referred to as the hidden layer. The information that is contained in the first and second layers of an RBF NN is combined in a manner that is linear in the third layer, which is responsible for the generation of the network output. A plain collection of sensory units makes up an RBF NN input layer. This layer is a part of an RBF neural network. As was seen, neurons, which are the fundamental components of the second-layer units, are nonlinear functions of the vectors that are introduced into them. Neurons are the building blocks of the second layer.

$$\varphi_i\left(x, c_i, \sigma_i\right) = \frac{e^{-\|x-c_i\|_2^2}}{\sigma_i^2}$$

where ‖.‖ represents the Euclidean norm, c_i denote the center and dispersion of the Gaussian function, and σ_i denotes the Gaussian function itself. The Euclidean norm is denoted by the symbol. The RBFNN results are given as

$$\hat{y}(x,\alpha,C,\sigma)=\sum_{i=0}^{n}\alpha_i\varphi_i(x,c_i,\sigma_i)$$

where n represents the total number of neurons in the network and α_i is the weight of the linear combiner at the output of the network.

It is very similar to training an RBFNN by utilizing the data set $D=\{x,y\}$ in order to identify the parametric vector $w=[\alpha,C,\sigma]$ that minimizes the training duration.

$$\Omega(x,w)=12\left\|y-\hat{y}(x,w)\right\|^2$$

The exploitation of the 0.5 factor is done in order to simplify the formulation of the training approach. This minimal least-square measures the error between the actual values and the desired values, demonstrates the goal of utilizing the RBFNN to get closer to the desired y-values. This criterion shows that the goal of utilizing the RBFNN is to get closer to the desired y-values [24-27].

The Levenberg-Marquardt (LM) methodology is generally regarded as the most successful way for resolving non-linear least-squares challenges. This is due to the fact that it takes use of the sum-of-squares character of the problem. This is as a result of the fact that it takes into consideration the character of the issue at hand. In order to train the RBFNN, a slightly altered version of the training criterion used for the LM is applied. In this particular iteration of the criterion, the hybrid non-linear/linear structure of the network is taken into consideration. Additionally, the modified criterion reduces the problem dimensionality, and it often achieves a higher rate of convergence. These are also benefits of using the modified criterion. In order to accomplish this, it makes it possible to apply appropriate methods that are specialized to computing parameter (linear, σ and non-linear c) while still working toward the goal of reducing a single explicit criterion. The parametric value that is considered to be the most significant to the problem is reduced as a result of the amended criterion in this way. When a predetermined number of repetitions have been completed, the training is terminated via the conventional approach of early termination.

4. Results and Discussions

The proposed RBF is compared with techniques such as random forests (RFs) and support vector machines (SVMs).The ability of all models, including logistic regression, to identify individuals who are at risk for cardiovascular disease (CVD) is generally identical, and as a consequence, their forecasts of persons who will acquire CVD are also comparable. This is due in part to a small number of observations in the data, which is reflected in an imbalance between the number of samples with zero labels and those with one label (7,012), which is a product of the process of data collection. The small number of observations is also reflected in an imbalance between the number of samples with zero labels and those with one label. The number of samples that have one label is noticeably greater than the number of samples that contain no labels at all.

The performance of the models that were built with in-lab variables only shows a slight improvement, with an increase of 0.7% in the number of outcomes that were predicted. It is possible to generate a prediction regarding whether or not a patient has cardiovascular disease based on the responses of patients to a survey.

It was important to scan the entire NHANES dataset for every conceivable variable in order to appropriately use data-driven modelling. This was a prerequisite for doing so. The data were structured in a way that made it easy to access them, and they were examined to ensure that they were consistent across all of the categories and time periods that were considered. The National Health and Nutrition Examination Survey (NHANES) is carried out on a yearly basis with the purpose of collecting a massive amount of data, some of which is categorized in a different way with each new round of the survey. It was discovered that the absence of responders was due to queries that leaned too much on the responses they gave to earlier ones (such as age, gender, or pregnancy status).
The data were insufficient due to the inconsistency of the NHANES data gathering methods, which caused the data to be inaccurate. Several other supplementary labels were utilized at varying points throughout the course of the cycles. As a direct consequence of the manual investigation that was carried out, the names of the variables were changed. Only 189 out of the database approximately 3900 variables were found to be valid in any of the NHANES cycles. After an analysis was finished, any datasets that were missing more than fifty percent of their values were removed from consideration.

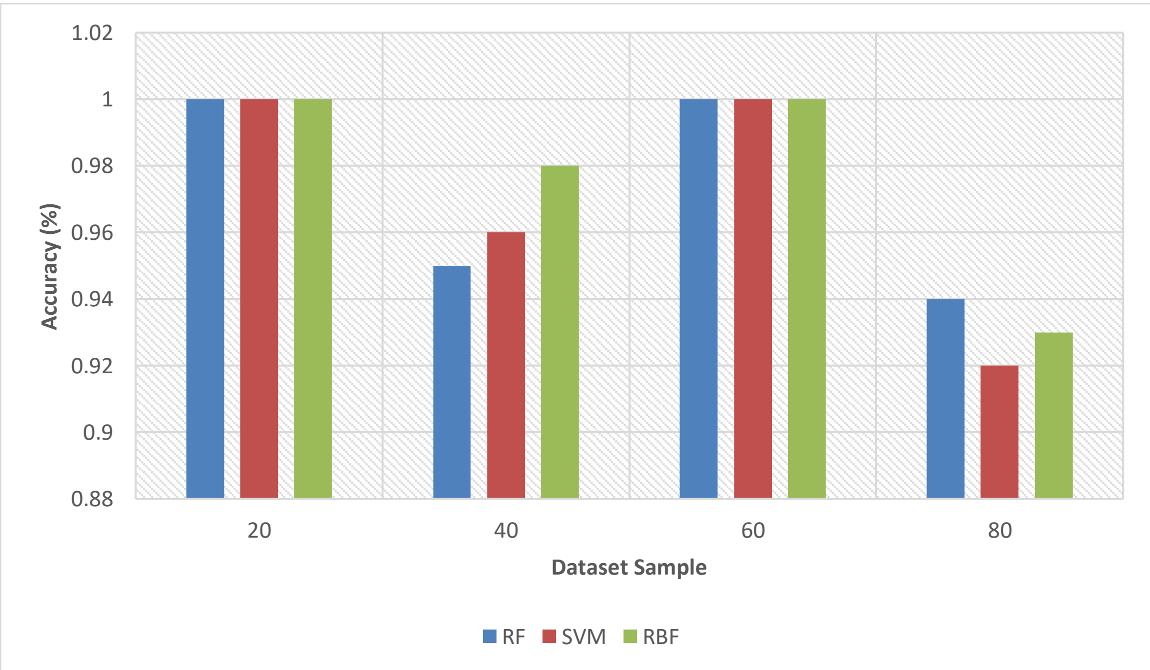

Figure 2: Accuracy

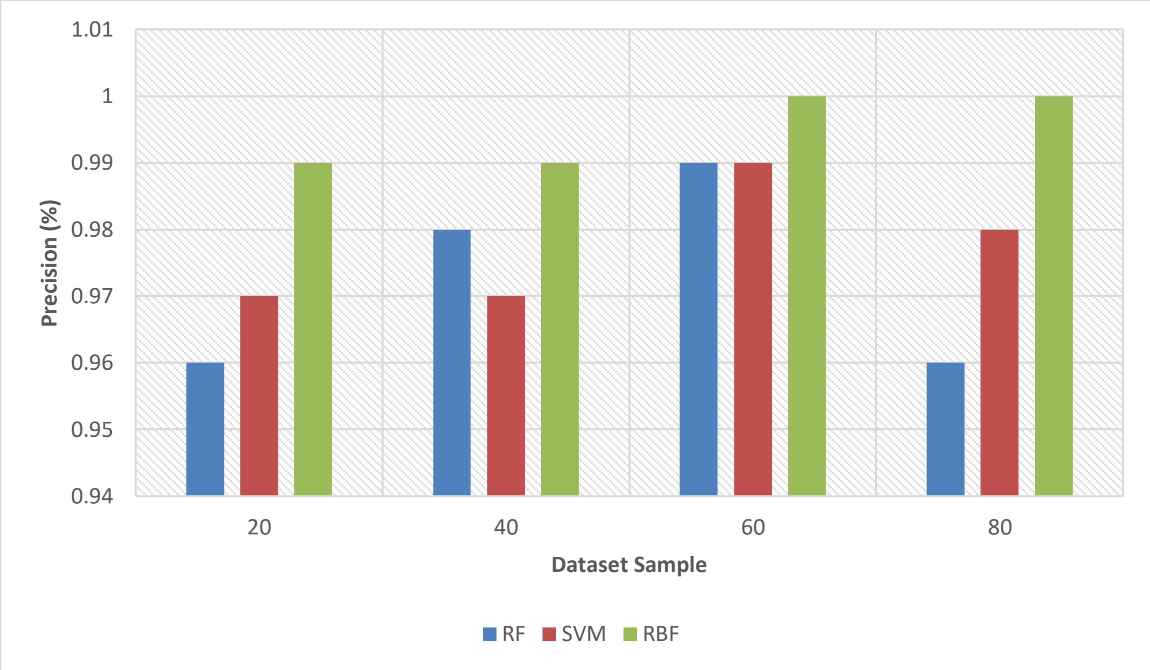

Figure 3: Precision

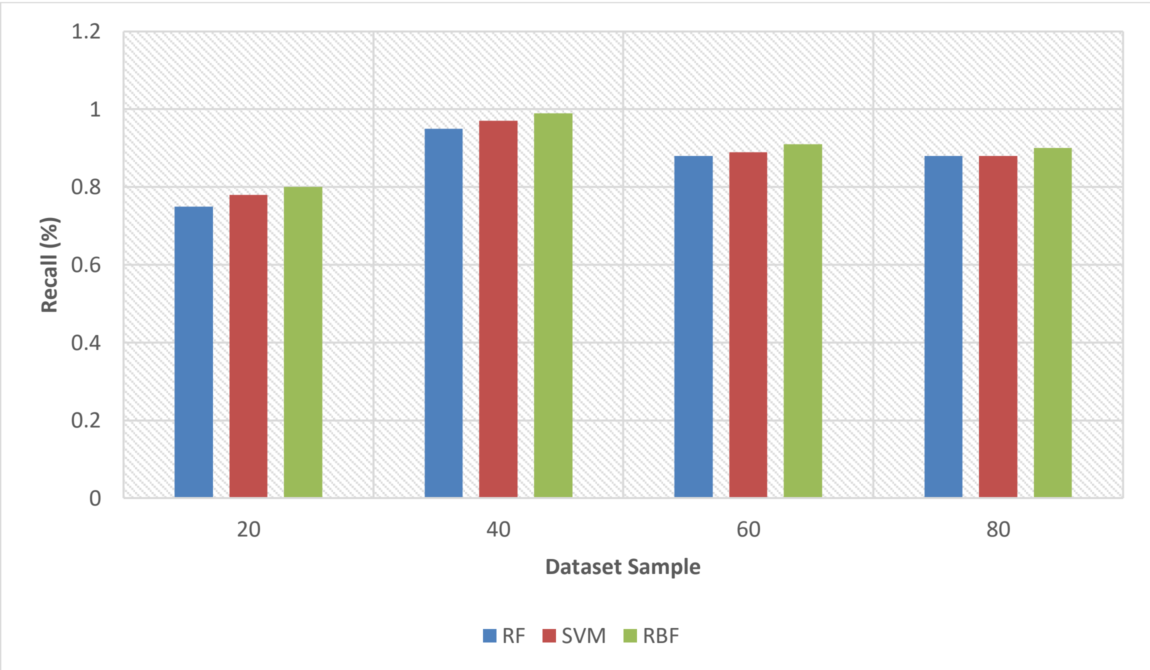

Figure 4: Recall

Widespread belief that inactivity can increase one risk of developing cardiovascular disease, the variables in the dataset that pertain to one level of physical activity were specifically chosen for inclusion. In every dataset, there is both a non-laboratory subset and a laboratory subset. The laboratory subset includes laboratory results, while the non-laboratory subset does not include laboratory results.

The results are used to encompass all feature variables in the dataset that originated from some type of bodily fluid analysis, such as blood or urine. The results shows that the proposed method achieves higher accuracy, precision, recall as in Figure 2 - 4.

5. Conclusions

There has been and will continue to be an increase in the incidence of cardiovascular diseases in both industrialized countries and emerging countries. In this paper, we design an Integrated Machine learning framework for Automated Vehicle Monitoring for CVD Patients. It is possible to utilize ML to identify whether or not this issue is the key factor in the development of following diseases. The research also studies the prospect that such models could be used to identify survey respondents who suffer from cardiovascular illness. This is done by analyzing the responses of those who participated in the survey. The findings of our study suggest that models trained by machine learning are able to accurately diagnose patients suffering from the diseases.

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