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A Proposed CNN Approach for Remote Monitoring of Elderly

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Abstract: The emergence of Smart Housing for Health aims to restore autonomy to elderly people with chronic illnesses, allowing them to remain at home. This concept requires an intelligent system that collects residents' data to monitor their activities and provide personalized services. This project addresses the issue of monitoring elderly people in a smart home environment while preserving their dignity and freedom. The proposed solution relies on integrating a deep learning-based system within the server, enabling the analysis of resident data and making real-time health-related decisions to adapt the provided services accordingly.

Keywords: *smart space; Internet of Things; monitoring systems; deep learning; convolutional neural network; machine learning; healthcare.*

1. Introduction:

The population of elderly people is on the rise and the number is expected to reach 20% of the total world population by 2050[1]. Virtually all the countries in the world are experiencing a surge of the proportion of elderly people. Therefore, to ensure progress in development, it is imperative to get ready for economic and social implications related to the elderly persons [2] and provide medical support, and enhance welfare for the elderly person through the development of innovative and pervasive smart technologies [3]. Wireless sensor networks have spurred smart homes, healthcare, environmental monitoring, and homeland security developments. Connecting these networks with Internet protocols has given rise to the Internet of Things (IoT), enabling everyday objects to connect to the Internet for real-time and ubiquitous monitoring [4]. The IoT is a framework that allows developers to connect several devices, systems, and technologies to achieve certain tasks [5] such as health monitoring. A large proportion of IoT technology directly builds on the motivation of monitoring our daily activities (e.g., monitoring steps and diets throughout the day). For instance, using a smart wristband, which is commonly used for monitoring health and fitness. Smartphones which are based on the electrocardiogram can be used to assess and analyze heart condition [6] Wearable sensor technologies and the IoT hold significant potential to enhance our lifestyle, particularly by offering healthcare monitoring systems that help track and manage health and fitness. Features like real-time communication enable data transmission and analysis by healthcare providers, allowing them to detect and respond to concerning behaviors or symptoms. Improving the efficiency and cost-effectiveness of healthcare is a key objective in modern society.

Monitoring patient's vital signs such as temperature, blood pressure and heart rate are one of the major aspects of today's healthcare services [7]. At the same time, healthcare institutions face mounting pressure, with an increasing number of patients, especially those suffering from age-related chronic illnesses. This combination of factors highlights the urgent need for innovative solutions to meet the complex needs of an aging population.

In this context, information technology emerges as an essential tool, offering promising possibilities for improving the quality of life for older adults and addressing the challenges they face [8]. From remote medical monitoring devices and health management applications to user-friendly interfaces for learning and communication, technological innovations open new perspectives for supporting and assisting seniors.

Therefore, we are proposing a system that enables continuous monitoring of elderly people's health in real-time to prevent chronic diseases, thus preventing hospitalization that burdens the

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healthcare systems and costs. This paper presents a system that utilizes Sensors for Smart Healthcare Monitoring systems for elderly people. The system accumulates patient's physiological data via wearable sensors (i.e., pulse, oxygen, etc.) elderly people in real-time. The data is transmitted to a data repository, where it will be stored and checked for any abnormality. Thus, any detection of a disorder in a patient's vitals will be reported to the patient's doctors and/or hospital in real time to act quickly and prevent several problems, such as a sudden heart attack. Providing such a system that can effectively monitor an elderly person's physiological activity at regular intervals could detect diseases and other complications earlier [9]. Especially, in the case of elderly people who are much likely to have a disorder in their physiological data [10]. It is an utmost necessity to develop new methods and technologies to improve health services for the elderly community at an affordable price with ease of use while ensuring maximum comfort and independence.

In recent years, development efforts to apply Deep Learning (DL) to smart homes have been continuously increasing. This is because DL can learn users' daily data from smart home devices and then help provide the most appropriate functions for the users' needs [11]. DL algorithms use neural networks that are deeply built up by a layering of base layers. It is a branch of machine learning (ML) that learns relationships from data in order to make decisions, and DL is used synonymously with the term Deep Neural Networks (DNN). This is a promising field of artificial intelligence that can provide increasingly satisfactory results as more data are collected [12].

Convolutional Neural Networks (CNN) is one of the most widely used DL algorithms. This model was reported by LeCun et al. in 1989 and showed successful performance in computer vision. [13] . CNN is excellent for feature extraction and classification. It has become dominant in image recognition, classification, and video recognition [12,14]. It represents an advanced type of neural network and programming model specialized in data processing. This algorithm is widely recognized and used in various fields such as computer vision, speech processing, and facial recognition. One of the main advantages of CNNs lies in their ability to automatically identify relevant features without requiring human supervision.

CNN models are composed of different layers that progressively process input data to extract increasingly abstract features. The four main operations illustrated in CNNs are:

- Convolutional Layer: This is the core of CNNs, typically integrated as the first layer. It consists of multiple matrices that facilitate the extraction of information from the input data's features to produce a feature map.
- Pooling Layer: This layer takes multiple feature maps as input to reduce the number of parameters in these matrices while preserving their essential features. I can be max pooling, mean pooling and sum pooling. The max pooling is the most commonly used type, as it is quick to compute and effectively simplifies the matrix by retaining the most prominent features.
- Activation Layer applies an activation function, such as ReLU (Rectified Linear Unit), to introduce non-linearities into the model
- Fully Connected Layer This layer is typically the final layer in CNNs. It connects every neuron in one layer to every neuron in the next layer, consolidating the extracted features into a classification or regression output. The fully connected layer interprets the high-level features generated by earlier layers to make predictions.

The rest of the paper is organized as follows. Section 2 provides an overview of related works. Section 3 presents the details of the proposed approach together with the models used. Section 4 describes the dataset, extracted features, and experimental results for monitoring elderly is healthy, Section 5 concludes the paper.

2. Related work:

With an aging population and rising stress levels, it is becoming necessary to integrate health monitoring systems capable of immediately analyzing patient data, detecting emergencies, and notifying medical personnel for a more in-depth diagnosis. Given our busy work schedules and the challenge of affording medical expenses, home health monitoring has become a practical solution for family health issues, allowing healthcare professionals to reach a wider market beyond traditional clinics. Thanks to this technology, patients can save significantly on healthcare costs, as they no longer need to travel to a health center or move for diagnosis, laboratory tests, or prescriptions. This also helps doctors provide timely and immediate healthcare services, potentially reducing emergency room admissions. Numerous individual projects around the world are exploring patient medical telemonitoring.

In[15] and [16] authors focused on a system for remotely monitoring blood glucose and blood pressure levels in diabetic patients using mobile phones. They highlighted the direct impact of hypertension on individuals with diabetes, finding that high blood pressure increases the risk of insulin resistance by 50%. In addition to hypertension, other factors like obesity, genetic predisposition, and type 2 diabetes can also contribute to insulin resistance. In [17], authors utilized the Internet of Things (IoT) as a simpler alternative for combining alarm and remote monitoring systems. They developed a remote alert system to monitor patients' blood pressure levels. This system uses sensors to collect various health parameters, which are stored through IoT and presented on a website for remote monitoring. According to the authors, sensors reduce human error and minimize system size, taking up less space in the room. A unique aspect of their solution is the alarm system for administering prescribed medication on time. Another beneficial feature is the notification system that sends alerts via email and SMS if any health parameter exceeds a set threshold, keeping the concerned authority informed of the patient’s status. [18] developed home blood pressure monitoring systems and evaluated large datasets on blood pressure in an uncontrolled home environment. They proposed techniques for analyzing these large collections of data. They studied the attributes of blood pressure trends for consecutive readings over several minutes. They showed results of blood pressure decreases every 10 to 25 minutes and also focused on one aspect of blood pressure, namely hypertension, while neglecting the other vital aspect of hypotension. Unrestricted hypertension poses an increasing challenge for healthcare systems worldwide. Given our lives and inability to cope with healthcare costs, home health monitoring becomes important and provides a practical solution to our health-related problems. Authors in [19] developed home blood pressure measurement systems that continuously monitor and record physiological parameters such as blood pressure, pulse rate, and falls of elderly individuals at home, among others. The demonstration involves using existing wireless technology to transmit data instead of transferring it manually. They developed an application that operates using sensors and a Bluetooth wireless device. It also presents the architecture of the receiver using a laptop and a mobile phone. In [20], a developed device to monitor temperature, blood pressure, and ECG. This home monitoring device uses sensors to detect physiological parameters. The transfer of these parameters to a microcontroller is carried out using integrated C code, which then displays the final result on an LCD screen. However, there is currently no notification function to send patient details to the doctor. Authors in [21] aim to develop an intelligent home health monitoring system that allows for the analysis of the patient's blood pressure and blood glucose measurements at home and notifies the healthcare provider in case of detected anomalies. To achieve this goal, a combination of conditional decision-making approaches and machine learning is utilized to predict the patient's status of hypertension and diabetes, respectively. Supervised machine learning classification algorithms are used to train a system capable of predicting the patient's diabetes and hypertension status. The paper [22] describes creating an intelligent health monitoring system specifically designed for the elderly. This system aims to detect their health status effectively. The system leverages wearable devices, which have gained popularity due to advancements in mobile communication technology. These devices are integral to providing real-time health monitoring. The authors in [23] investigated the living conditions of the elderly, which informed the design of the smart home system tailored to their needs. The system is based on the Internet of Things (IoT) and includes features for daily data collection, real-time data transmission, and prompt alarms for emergencies the system integrates various smart devices, such as the Xiaomi Mijia Bluetooth Hygrothermograph for temperature and humidity monitoring, and the Xiaomi Smoke Guard for fire detection. The system includes an alarm mechanism that alerts users and relevant personnel in case of potential safety hazards, ensuring a safe living environment for the elderly. In [24] the system utilizes the Internet of Things (IoT) for continuous monitoring of elderly individuals, particularly those living alone or in rural areas. It tracks various health parameters, including ECG (electrocardiogram), blood oxygen levels, and fall detection. This is achieved through different wearable devices. A chest strap is employed to read ECG signals. A wrist strap monitors the oxygen level in the blood. To minimize false alarms, the system integrates three modules that work together to provide accurate monitoring. The project's goal in [25] is to create a working prototype for geriatric health monitoring using various sensors and send alert messages to doctors and family members in the event of abnormal vital signs. The sensors used in this smart health monitoring system include a heartbeat sensor, a GSR for stress detection, a temperature sensor, and an accelerometer sensor for fall detection as well as for step counting, Along with these sensors GPS Tracker, Arduino Nano, node MCV, and a display are used.

3. Proposed system:

Our system consists of two interfaces: the server side and the client side. The client-side includes two users: the patient and the paramedic. Each has a specific role: the patient sends their samples after registration or authentication, while the paramedic receives the alert as an audible signal. This alert is sent in the case of an abnormal situation. The server side processes and analyzes the patients' conditions.

The system shown in Figure 1 allows patients to create an account by providing personal information such as their first name, last name, age, and phone number. Once registered, the patient can access their account using a username and password through the authentication feature. Once logged in, they can access their dashboard, where they can securely enter and view their health data.

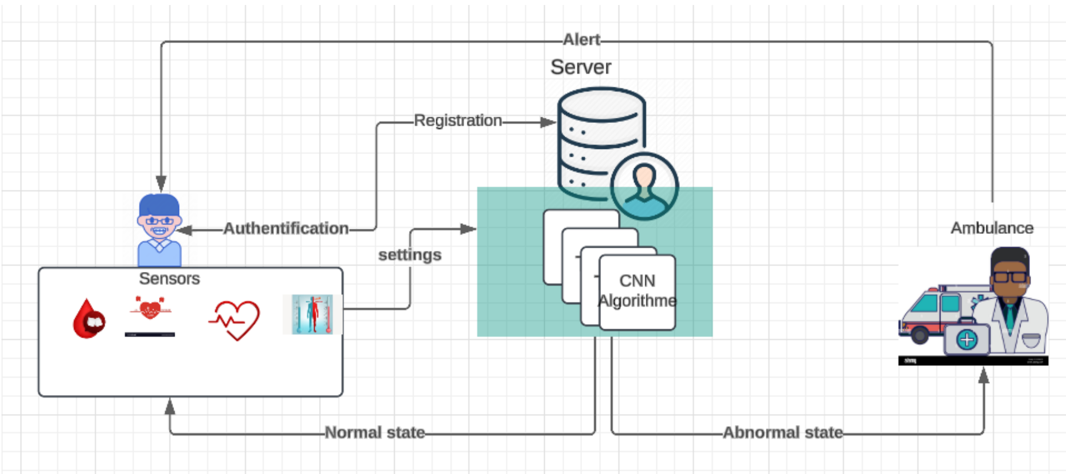


Figure 1 : Architecture of the proposed CNN Model to monitor elderly health

The primary action taken by the patient is to send their samples to the server for data evaluation and processing. These samples include measurements such as blood glucose level (BGL), blood pressure, heart rate, body temperature, and more. This information is processed quickly and efficiently by the system. If an analysis reveals an abnormal health condition, the system automatically triggers an alert. This alert is sent to local emergency services, including paramedics near the patient's home, to enable an immediate response if necessary. This responsiveness ensures the safety and well-being of patients in cases of medical emergencies.

The sequence diagram shown in figure 02 allowed for a detailed conceptualization and modeling of the functioning of the medical monitoring system, taking into account the specific needs and complex interactions unique to this field.

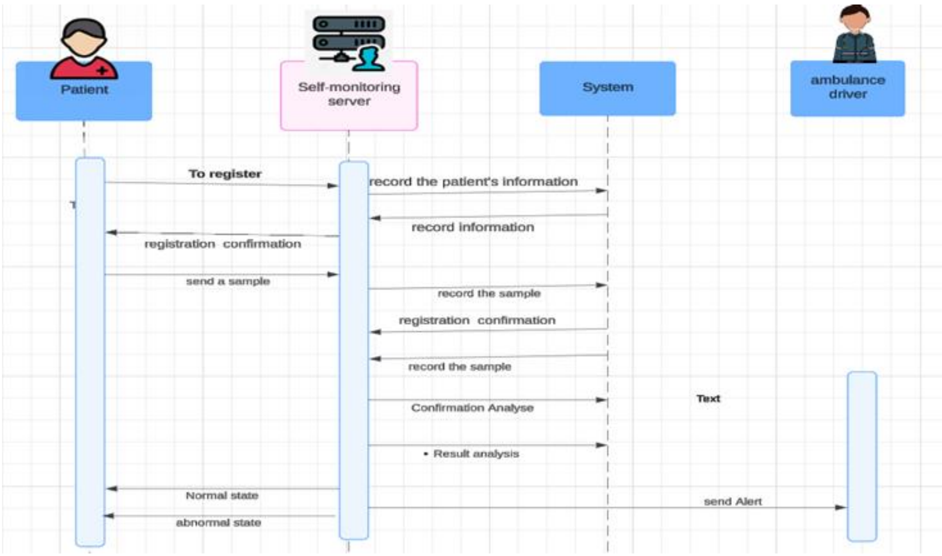


Figure 2 : sequence diagram detailed the functioning of the medical monitoring system

Dashboard Access: After successfully authenticating, the patient accesses their personal dashboard through the client interface of the system.

Display of Data Entry Interface: The system displays an interface allowing the patient to enter values for their health data samples, such as blood glucose level, and blood pressure, Health Data Entry: The patient enters the values of their samples in the corresponding fields of the interface.

Data Saving: Once the data is entered, the patient chooses to save it in the system for future tracking.

Data Submission to Server: The patient selects the "Save" icon to send the entered health data to the central server.

Data Processing: The server receives the data for evaluation and processing, using deep learning algorithms to detect any anomalies.

4. Implementation:

4.1 Data Preprocessing (Normalization)

: In our system, we applied a crucial data normalization step using the StandardScaler class from the scikit-learn library . This method is essential for preparing data before using it in a machine learning model, especially for CNN models, which can be sensitive to the scale of input features. Normalization involves transforming the data so that each feature has a mean of 0 and a standard deviation of 1 as shown as figure . This process is carried out in two main steps:

- Calculating the Mean and Standard Deviation: For each feature in our dataset, we first calculate the mean (μ) and the standard deviation (σ). These statistics are essential for understanding the data distribution.
- Data transformation: Once the mean and standard deviation are calculated, each value x in the feature is transformed according to the following formula:

$$Z = (x - \mu) / \sigma$$

This is especially important in our case, where features such as blood pressure, glucose level, and body temperature are measured in different units. After normalization, the data was ready to be used as input in the CNN model, thereby ensuring better performance and faster convergence of the learning algorithm.

	Blood Glucose Level(BGL)	Diastolic Blood Pressure	Systolic Blood Pressure	Heart Rate	Body Temperature
0	-0.389026	-0.576346	-0.024307	0.622107	1.495428
1	-0.365766	-0.576346	0.105561	1.006373	1.495428
2	-0.598368	-0.162056	-1.063249	-1.011020	1.495428
3	-0.598368	0.114138	-0.413910	0.429975	1.495428
4	0.099438	2.599880	3.352257	0.045709	0.186716

Figure 3 : Normalisation of data

4.2 Data Splitting into Training and Testing Sets:

Dividing the data is essential for evaluating model performance. For this step, we used the train_test_split function from the scikit-learn library. This function divides a dataset into two subsets: a training set and a test set. The training set is used to train the model, while the test set is used to evaluate the model’s performance on unseen data. In our case, we trained the model on 80% of the data and tested it on the remaining 20% to obtain a realistic estimate of the model's ability to generalize to new data. This division is crucial for preventing over fitting, where a model performs well on training data but poorly on new data.

4.3 Data Reshaping for the CNN Model

This step reshapes the input data to prepare it for CNN model. The goal is to adjust the data to the required format for 1D convolutional layers. Without this reshaping, the CNN would not know how to process the data, as it expects a 3-dimensional input structure (samples, time steps, and features). Reshaping ensures the data is correctly formatted so that the convolutional layers can apply their filters effectively. This preparation is crucial in enabling the CNN to identify patterns within sequential data, making it highly applicable in fields like time-series analysis, where the 1D CNN can detect trends and correlations across input sequences.

4.4 CNN Model Construction

The model is built using Keras's Sequential class, which allows layers to be stacked in a linear structure. It comprises the following layers: Conv1D: A 1D convolutional layer with 64 filters and a kernel size of 2, using ReLU activation to extract local features from the input data. MaxPooling1D: Reduces data dimensionality with a window size of two, retaining essential features and reducing computational load. Flatten: Converts the output into a 1D vector for the dense layer. Dense: A fully connected layer with 50 neurons and ReLU activation, designed to combine the features extracted by the convolutional layers. Output: A single neuron output layer with sigmoid activation for binary classification.

5. Testing and evaluating

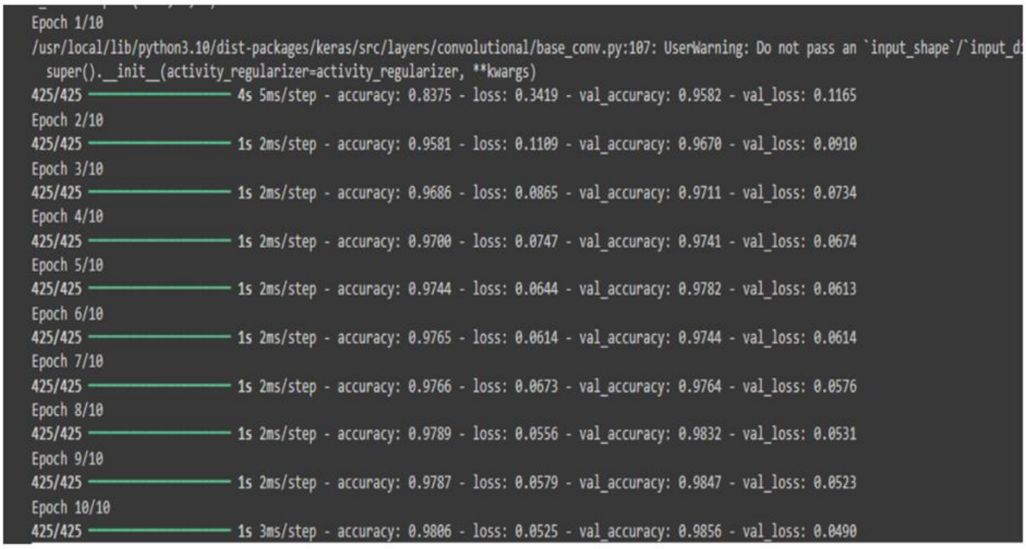
The model is trained on the training dataset (X_train, y_train) over 10 epochs. After each epoch, the model is evaluated on the validation set (X_test, y_test) to assess its ability to generalize to new data. This approach provides feedback on the model's performance at each stage, helping monitor and prevent potential overfitting. The displayed results seen in the figure 4 show the evolution of training accuracy and loss, along with validation accuracy (val_accuracy) and validation loss (val_loss) over 10 epochs, as follows:

Epoch 1/10: Training begins with an accuracy of 83.75% on the training set and 95.82% on the validation set. The initial loss is relatively high (0.3419), which is typical at the start of training.

Epochs 2-5/10: The model gradually improves its performance. By epoch 5, the training accuracy reaches 97.44%, with a stable validation accuracy at 97.82%. The decrease in loss indicates that the model is making fewer errors.

Epochs 6-10/10: The model continues to show slight improvement, achieving a training accuracy of 98.06% by epoch 10 and a validation accuracy of

98.56%. Loss values remain low for both training and validation, with a final validation loss of 0.0490, indicating good generalization and minimal overfitting.



```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_d
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
425/425 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.8375 - loss: 0.3419 - val_accuracy: 0.9582 - val_loss: 0.1165
Epoch 2/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9581 - loss: 0.1109 - val_accuracy: 0.9670 - val_loss: 0.0910
Epoch 3/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9686 - loss: 0.0865 - val_accuracy: 0.9711 - val_loss: 0.0734
Epoch 4/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9700 - loss: 0.0747 - val_accuracy: 0.9741 - val_loss: 0.0674
Epoch 5/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9744 - loss: 0.0644 - val_accuracy: 0.9782 - val_loss: 0.0613
Epoch 6/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9765 - loss: 0.0614 - val_accuracy: 0.9744 - val_loss: 0.0614
Epoch 7/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9766 - loss: 0.0673 - val_accuracy: 0.9764 - val_loss: 0.0576
Epoch 8/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9789 - loss: 0.0556 - val_accuracy: 0.9832 - val_loss: 0.0531
Epoch 9/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9787 - loss: 0.0579 - val_accuracy: 0.9847 - val_loss: 0.0523
Epoch 10/10
425/425 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9806 - loss: 0.0525 - val_accuracy: 0.9856 - val_loss: 0.0490
```

Figure 4: the evolution of the training dataset over 10 Epoch

As shown in Figure 5, the loss steadily decreases, indicating effective learning as the model minimizes error. The validation loss closely follows this trend, suggesting that the model generalizes well without significant overfitting. The figure demonstrates a consistent increase in accuracy, with the model reaching over 98% for both training and validation sets by the end. This improvement confirms that the model is learning effectively and becoming increasingly precise with each epoch of training.

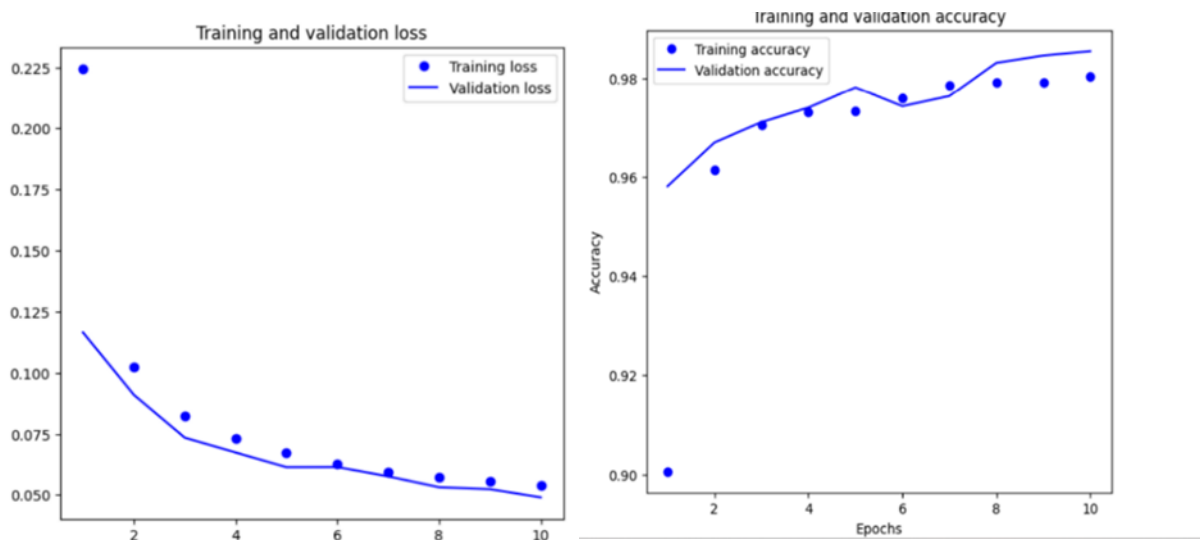


Figure 4 : illustrates the model's performance over epochs, showing both loss and accuracy for the training and validation sets

These trends, with aligned loss reduction and accuracy improvement across both sets, indicate robust performance and stable generalization to new data. In the context of CNN model evaluation for classification, four key metrics are frequently used:

Accuracy: Represents the percentage of correct predictions out of the total predictions. It gives a general overview of how often the model makes correct classifications, but it can be misleading if the classes are imbalanced.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total Number of Predictions}}$$

Recall (Sensitivity): Measures the model's ability to correctly identify all true positives. It's particularly important in contexts where missing positive instances (false negatives) is costly, such as in medical diagnoses. High recall means that the model successfully identifies most relevant cases.

$$Recall = \frac{\text{Number of True Positives}}{\text{Number of True Positives} + \text{Number of False Negatives}}$$

Precision: Indicates the proportion of true positives among all positive predictions made by the model. Precision is critical in cases where false positives (incorrectly classified positives) need to be minimized, as in spam detection.

$$Precision = \frac{\text{Number of true positive}}{\text{Number of true positive} + \text{Number of false positive}}$$

F-score (F1 Score): The harmonic mean of precision and recall, providing a balanced measure when both recall and precision are important. It's especially useful for imbalanced datasets, as it captures the balance between false positives and false negatives.

$$\text{F} - \text{score} = 2 * (\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}})$$

Each metric provides insight into the model's performance from different perspectives, helping to understand both its strengths and areas that might require tuning or further training. For a CNN in classification tasks, combining these metrics gives a more nuanced view than relying on accuracy alone. According to Figure 6, the model shows excellent overall performance: High accuracy for both classes, especially for class 1, which is predicted with an accuracy of 99%. High recall, meaning the model detects instances of both classes well. High F1-Score, indicating a good balance between precision and recall. Confusion matrix: The majority of predictions are correct, with very few errors (18 false positives and 31 false negatives).

	precision	recall	f1-score	support
0	0.95	0.97	0.96	673
1	0.99	0.99	0.99	2721
accuracy			0.99	3394
macro avg	0.97	0.98	0.98	3394
weighted avg	0.99	0.99	0.99	3394

```
[[ 655   18]
 [  31 2690]]
```

Figure 5 : Performance evaluation of CNN Model

Figure 7 illustrates the model's predictions on the test data, comparing them to the actual values (State_True). Observing the predicted values (State_Predicted) alongside the real labels shows that the model's predictions largely match the true values, supporting the positive performance seen in prior classification metrics. This consistency between predictions and actual values indicates that the model generalizes well on unseen data, maintaining a high accuracy and effectively capturing patterns in the dataset. This alignment reaffirms the model's robustness and suggests reliability in practical applications, especially in scenarios requiring high classification accuracy.

```
Données de test avec les prédictions :
   Blood Glucose Level(BGL)  Diastolic Blood Pressure  \
0                      79.0                      73.0
1                      68.0                      67.0
2                     112.0                      83.0
3                      92.0                      87.0
4                     106.0                      83.0

   Systolic Blood Pressure  Heart Rate  Body Temperature State_Predicted  \
0                    118.0        80.0              98.0         Natural
1                    115.0        89.0              96.0         Unatural
2                    110.0        90.0              97.0         Natural
3                    121.0        89.0              96.0         Unatural
4                    119.0        88.0              97.0         Natural

  State_True
0    Natural
1   Unatural
2    Natural
3   Unatural
4    Natural
```

Figure 6 : The model's prediction of the test data

6. Conclusion

The implementation and evaluation of our computer system for monitoring the health of elderly people with chronic illnesses produced significant results. By using languages and software, particularly Python in Google Colab for developing the deep learning model, we were able to create a robust architecture. This architecture has two main interfaces: a server side for data analysis and a client-side involving the patient and the doctor. The use of advanced methods such as CNNs (Convolutional Neural Networks) was demonstrated effectively during model evaluation in various scenarios. The intuitive client-side interface allows the patient to enter their data and the doctor to accurately analyze the results. The server, using deep learning through CNNs, processes the data and triggers audible alerts when an abnormal condition is detected. This experience shows that home automation-based monitoring can improve the care of elderly people with chronic illnesses. The results obtained pave the way for future research and applications in healthcare and home assistance.

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