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INFORMATION TECHNOLOGY IN SPORTS SESSION

OPTIMAL SENSOR CONFIGURATION FOR BODY TEMPERATURE ESTIMATION IN SMART CLOTHING USING MACHINE LEARNING MODELS

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Abstract:

Modern wearable technologies enable the collection of physiological and environmental data, which represents a significant potential for application in sports monitoring, analytics, performance modeling and even injury prevention. Although sensors allow for direct measurement, their values often deviate due to the influence of external conditions and sensor position. The unique materials, sensor technology, ethical issues, the benefits and drawbacks of using smart clothing in sports and medicine have all been discussed in the presented research, with particular emphasis on the fact that the analysis of data obtained from multiple sensors is challenging due to the existence of nonlinearity, variability and the presence of various noise. In order to improve the accuracy of the estimation, RF, SVM and FFNN have been applied in this paper. Machine learning models have been developed with different configurations of input variables, including individual temperature sensors, as well as their combinations and the performance of all models was evaluated using RMSE and R^2. The assessment was carried out in a regression framework, while the results were additionally classified into three classes based on medically defined thresholds. The obtained results confirm that a high estimation accuracy can be achieved with a reduced number of sensors, which enables the simplification of the system and the reduction of implementation costs. Also, it is shown that the conclusions are consistent across different models, which indicates the robustness of the approach. The paper discusses the application of systems in sports for monitoring athletes' physiological conditions, optimizing training, and detecting risky conditions.

Keywords:

Smart Clothing, Wearable Sensors, Machine Learning, Multisensor Data, Temperature Estimation.

INTRODUCTION

Modern technological development significantly affects the improvement of the quality of life, especially in the field of health care. One of the most significant directions of development is the integration of electronic components and sensors into textile materials, which led to the emergence of smart clothing [1]. Smart clothing is a subset of wearable technologies and is based on the integration of flexible sensors, conductive fibers and advanced materials that enable long-term and reliable application in everyday conditions [2].

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As a result, people are becoming more sophisticated and beginning to look for the most practical and technologically advanced products for everyday use [3]. Such systems enable continuous, non-invasive and real-time monitoring of the user's physiological parameters, such as body temperature, heart rate and other vital indicators. A variety of ambient stimuli can be sensed, reacted to, and interacted with by smart e-textiles, which can then use manual pre-programmed processing to complete a task [4]. The development of nanotechnology and flexible electronics has further improved the capabilities of these systems, enabling the miniaturization of components and increasing their resistance and functionality [5]. Smart clothing is becoming more popular and data show that the expected industry growth will be 26.2% from 2020. to 2027. [6]. New textile engineering technologies have made clothes that can handle daily wear without affecting the sensors that are built into them [7].

Less movement, physical activity and the popularization of unhealthy food in combination with stress and pollution cause more and more cardiovascular diseases, which are the leading cause of death in the world, and account for about a third of all deaths. Close to 85% of these deaths are the result of heart attacks and strokes, and more than three-quarters occur in low- or medium-developed countries. It can be considered a major indicator of a global problem that is increasing due to risk factors such as diabetes, obesity, hypertension and unhealthy habits [3].

In this context, continuous monitoring of physiological parameters, including body temperature and pressure, plays an important role and big benefit in the early detection of health abnormalities and overall condition assessment. Another advantage of smart clothing is that it can monitor parameters during the postoperative course of home treatment for patients who have already had surgery and, in the event of an emergency, immediately alert doctors or caregivers.

Despite numerous advantages, the application of smart clothing also raises numerous ethical issues, especially in relation to privacy and data security, while the disadvantages include measurement reliability, maintenance, as well as durability and resistance of embedded sensors. Also, a question arises: who should analyse this type of data: humans (engineers or doctors) or machines? A big challenge is the processing and interpretation of collected data, which are often nonlinear, noisy and depend on a large number of factors.

In this context, artificial intelligence methods, especially machine learning (ML), represent an effective solution for modeling and such complex data. This paper discusses the application of the feedforward neural network (FFNN), random forest (RF) and support vector machine (SVM) models for body temperature estimation based on data collected from the smart clothing system. Special focus is on the analysis of the influence of different combinations of input sensors on the classification performance, thus enabling the identification of the optimal system configuration for practical application.

2. UNIQUE MATERIALS AND SENSOR TECHNOLOGY

There are many different ways to integrate sensor-equipped materials into clothes. Figure 1 shows how electronic parts can be added to textile materials, from simple attachment systems (like clips and belts) to magnetic and flexible electronic solutions. Finally, there are also fully integrated systems, but the standardization factors and the ability of different devices to work together are sometimes challenging to combine [8]. Usually, the more integrated a system is, the better it works and (in most cases) the more comfortable it is for the user. These materials allow electrical connections and sensors to be built into the textile while still being flexible and able to withstand wear and washing [9], such as nanomaterial-enhanced fibers and stretchable conductive bonds. They ensure stable skin contact and reliable measurement during user movement [10].

The system of smart clothing includes several types of sensors that enable comprehensive monitoring of the body's condition. Textile ECG sensors, based on woven electrodes and configurations with dry electrodes, allow the measurement of the electrical activity of the heart without the need for additional gels [11]. In addition to them, biological sensors such as galvanic skin response (GSR) sensors, respiratory sensors and skin temperature sensors are used, which provide additional information about the physiological state of the user [12]. Resistive textile sensors made of conductive fabrics can pick up signals of strain, moisture, and biopotential [13]. New technologies like AgNW/PEDOT conducting fibers are great for long-term wearable use because they are flexible, strong, and always work well electrically.

Data processing can be done with both edge computing, which extracts features in real time or cloud-based analytics, which requires more advanced modeling and long-term monitoring. These systems can continuously monitor the heart and blood vessels, including heart rate and rhythm analysis. However, they work best when they use more than one sensor. In this case, skin temperature sensors give useful information and play a vital role in physiological stress, fatigue, and early signs of possible health problems. The position (part of the body) where the sensor is placed also plays an important role, because the conditions for measurements are different (depending on the movement type or level of sweating).

3. DATASET DESCRIPTION

This paper uses a database taken from reference [15], which contains detailed physiological and ambient data collected using smart clothing with integrated temperature sensors. This database reflects the behaviour of the wearable system in real environmental conditions. The data was collected using smart noninvasive sensors, suitable for long and comfortable wearing. This enables continuous monitoring of temperature in the various and dynamic conditions. The database includes temperature measurements from different regions: chest (sensor1), abdomen (sensor2), back (sensor3) and armpit (sensor4). There is also additional information about ambient conditions and system status.

The total data set contains N = 3000 samples, with each record including a time stamp, temperature values from all sensors, outdoor temperature, humidity level, physical activity level, battery voltage and subjective comfort rating. In order to better understand the characteristics of the database, graphical analyses were used, as shown below.

Figure 2 shows multisensor temperature measurements collected from different body regions, illustrating the variability and correlation between sensors. All sensors follow a very similar pattern over time. This means that the measurements are not chaotic and that all sensors register the same basic thermal dynamics of the system (human body). The temperature range is 35 to 38°C, but the highest concentration of spots is approximately between 35.5 and 37 °C. Extreme values exist, but they are not dominant. Also, there is a scatter of points around the main trend, meaning that there are small noise between sensors, but measurements from different locations on the body are highly correlated, although not exactly the same. In this approach, a sensor placed in the armpit area is used as a reference measure of body temperature, while other sensors provide additional information from different parts of the body.

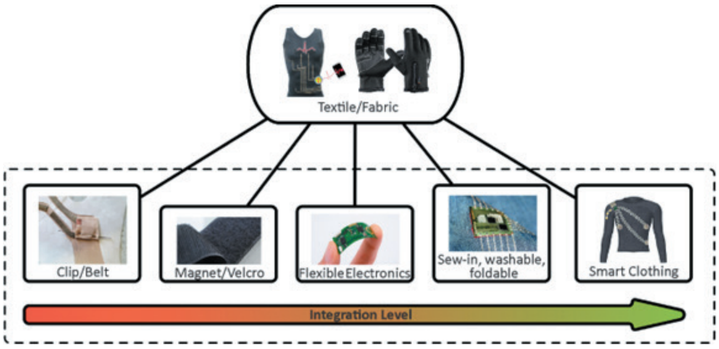

Figure 1. Integration levels of smart clothing. Adapted from [14]

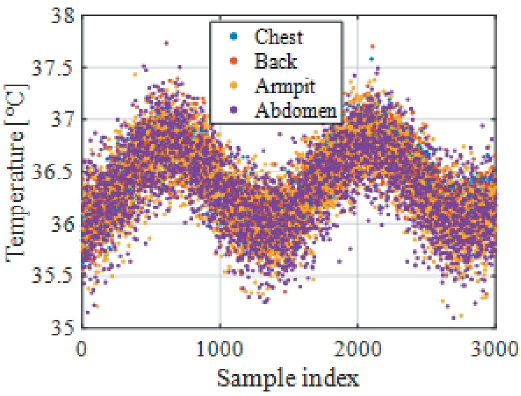

Figure 2. Multisensor temperature measurements

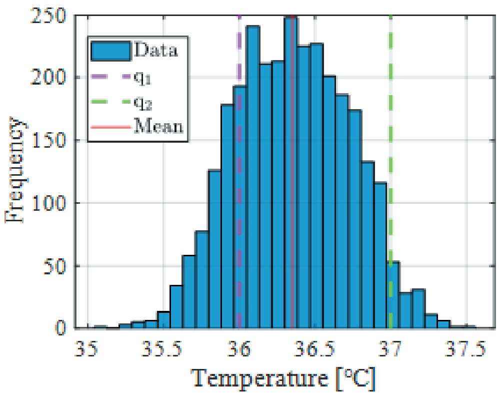

Figure 3. Distribution of reference body temperature

These sensors require precise positioning, significantly depend on the quality of contact with the skin and can be uncomfortable for the user, which is why they can be an unstable and impractical solution in wearable systems. The machine learning model learns the interrelationship between sensor readings from different locations and the reference temperature, thereby enabling reliable estimation without relying directly on the armpit sensor. In this context, the reference sensor is used exclusively during the training phase of the model, while after that the model can function independently, thus achieving greater practicality, stability and comfort in the application of the system. Figure 3 shows the temperature distribution histogram of the target sensor$_4$. Dashed vertical lines indicate medicine thresholds q_1 and q_2, based on which three classes were formed: low, normal and high temperature.

4. MACHINE LEARNING MODELS

This paper proposes three different algorithms to predict temperature: random forest (RF), support vector machine (SVM) and feedforward neural networks (FFNN), where different combinations of sensors were used as inputs.

4.1. RANDOM FOREST

Random forest represents a powerful and adaptive ML algorithm. It creates many decision trees during the training, where each tree is based on a different data subset. This methodology prevents overfitting and because of that created models usually have good generalization. In a classification task, the final decision is based on the most common class predicted by all the trees.

For regression, the final output is the average of the predictions [16]. In this paper, a model is constructed using 100 trees (**NumTrees=100**).

The maximum number of splits (**MaxNumSplits**) isn't limited, allowing full growth. The minimum leaf size is set to 5 (**MinLeafSize=5**), while the number of predictors sampled at each split is equal to the total number of input variables (**NumVariablesToSample=N$_{\text{input}}$**).

4.2. SUPPORT VECTORS

Support uses a kernel function to map input data into a higher-dimensional space. It determines a function that approximates the target values within a predefined tolerance [17]. In this research, a radial basis function kernel (**KernelFunction = RBF**) was used. Input data were standardized (**Standardize = true**), while the remaining parameters were set to their default MATLAB values.

4.3. FEEDFORWARD NEURAL NETWORKS

The feedforward neural network architecture comprises an input layer, an output layer, and one or more hidden layers containing interconnected neurons (in this case, **2 hidden layers with 5 neurons**). The adaptable weighted connections between neurons enable information flow between layers. By employing nonlinear activation functions in the hidden layer (**sigmoid activation functions**), the neural network, trained with the Levenberg–Marquardt (**trainlm**) algorithm, exhibits universal approximating capabilities [18].

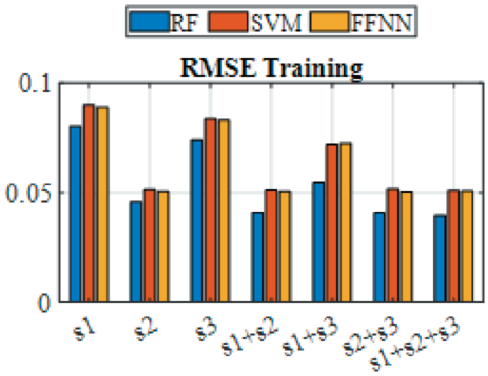

Figure 4. Root mean square error on training data

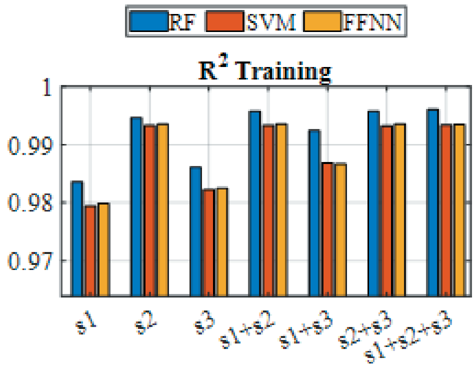

Figure 5. Coefficient of determination on training data

5. RESULTS

The results on the training set confirm the stability of the model. Figure 4 represents root mean square errors (RMSE) for all combinations of the models. The RF model shows slightly better performance on training data (70%), while the SVM and FFNN models are more consistent between training and test results. Sensor$_2$ individually performs very well in all models, with RMSE values below 0.1 and a coefficient of determination R^2 greater than 0.98, Table 1. Sensor$_1$ shows the worst performance, with a higher RMSE (goes up to 0.09). Combinations of sensors generally improve the performance of the model on the training set, which can be seen from the determination coefficient in Figure 5. Root mean square errors (RMSE) are lower in training than in the test set. The results on the test set show that sensor$_2$ still performs very well individually in all models, with RMSE values around 0.05 and R^2 greater than 0.97. As expected, due to the worst training, sensor$_1$ shows the weakest performance, with significantly higher errors (RMSE ≈ 0.09). Combinations of sensors generally improve the performance of the model, which can be seen from Figures 6 and 7. Combinations with sensor$_2$, which give the best results for all models, stand out in particular. Overall, all models achieve high accuracy on the test set, Table 2, with sensor$_2$+sensor$_3$ as the most effective input combination, and RF as the most successful model.

Compared to using only sensor$_2$, this combination achieves a slight performance improvement (decrease in RMSE from 0.0534 to 0.0515), indicating that sensor3 brings an additional but relatively small amount of useful information. The results show that one of the sensors achieves great performance when used individually, while adding additional sensors does not lead to a significant improvement in accuracy. However, the introduction of the third sensor can be justified from the aspect of system reliability, because it enables the application of the "two out of three" logic, during which it is possible to detect and eliminate a defective sensor in the event of its failure.

As shown in Table 1 and Table 2, RF obtains the best results (highlighted in green), followed by FFNN. The best results for each method are indicated in bold. Although all of the models were trained to estimate body temperature, sometimes for clinical interpretability, it is useful to do classification. 60% of the test data (predicted and actual temperatures) were subsequently discretized into three categories based on medically defined thresholds: q_1 = 36°C and q_2 = 37°C (Figure 3). Such a classification enables a clearer interpretation of the results in the clinical context and facilitates decision-making regarding the assessment of the health condition. Figures 8 and 9 show confusion matrices for the best RF and FFNN models.

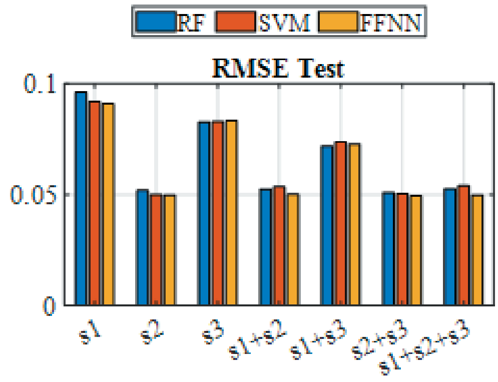

Figure 6. Root mean square error on test data

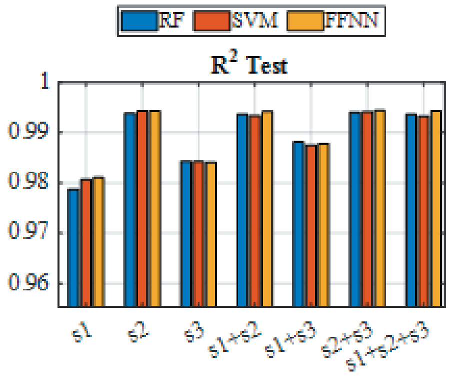

Figure 7. Coefficient of determination on test data

Table 1. Training results

Input	RF (RMSE / R²)	SVM (RMSE / R²)	FFNN (RMSE / R²)
sensor$_1$	0.0816 / 0.9838	0.0902 / 0.9802	0.0893 / 0.9806
sensor$_2$	0.0452 / 0.9950	0.0502 / 0.9939	0.0500 / 0.9939
sensor$_3$	0.0746 / 0.9865	0.0837 / 0.9829	0.0830 / 0.9832
sensor$_1$+sensor$_2$	0.0405 / 0.9960	0.0506 / 0.9938	0.0498 / 0.9940
sensor$_1$+sensor$_3$	0.0558 / 0.9924	0.0726 / 0.9872	0.0716 / 0.9875
sensor$_2$+sensor$_3$	0.0401 / 0.9961	0.0509 / 0.9937	0.0499 / 0.9939
sensor$_1$+sensor$_2$+sensor$_3$	**0.0395 / 0.9962**	0.0512 / 0.9936	**0.0493 / 0.9941**

Table 2. Test results

Input	RF (RMSE / R^2)	SVM (RMSE / R^2)	FFNN (RMSE / R^2)
sensor$_1$	0.0950 / 0.9774	0.0921 / 0.9788	0.0911 / 0.9793
sensor$_2$	0.0534 / 0.9929	0.0528 / 0.9930	0.0532 / 0.9929
sensor$_3$	0.0800 / 0.9840	0.0829 / 0.9828	0.0820 / 0.9832
sensor$_1$+sensor$_2$	0.0533 / 0.9929	0.0527 / 0.9930	0.0525 / 0.9931
sensor$_1$+sensor$_3$	0.0675 / 0.9886	0.0723 / 0.9869	0.0718 / 0.9871
sensor$_2$+sensor$_3$	0.0515 / 0.9934	0.0529 / 0.9930	0.0527 / 0.9931
sensor$_1$+sensor$_2$+sensor$_3$	0.0521 / 0.9932	0.0534 / 0.9929	0.0525 / 0.9931

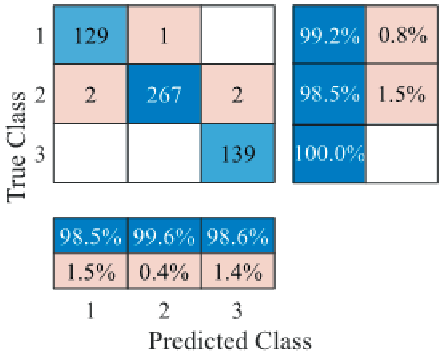

Figure 8. Confusion Matrix (RF)

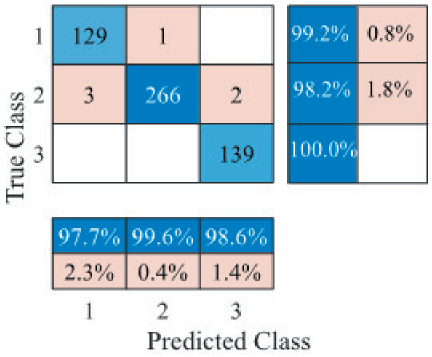

Figure 9. Confusion Matrix (FFNN)

Models achieve very high accuracy and show good ability to differentiate health conditions based on temperature. The differences between the models are minimal, but the RF model shows a slightly more stable performance for class 1, while the other classes are practically identical.

6. CONCLUSION

In order to determine the optimal position of the sensor in wearable clothes, different configurations of temperature measurement were analyzed. Although temperature sensors allow direct measurement, their values do not always represent the exact internal body temperature, but the local temperature at the point of measurement. The read values are significantly affected by external conditions, as well as the position and quality of the sensor contact, which can lead to deviations from the actual temperature. For this reason, machine learning models have been applied, which enable the learning of a nonlinear relationship between sensor readings and actual body temperature. In this way, the model performs an implicit calibration of the sensor, compensates for the influence of noise and external factors, and enables a more precise temperature assessment. The obtained results indicate that the sensor on the abdomen achieves the best performance when used individually, which confirms its greatest informativeness compared to other sensors.

Further analysis of combinations of multiple sensors did not show a significant improvement in model accuracy. The reason for this lies in the high mutual correlation of the sensors, which indicates a pronounced redundancy of the measured signals. In such conditions, adding additional sensors does not bring new information, but only increases the complexity of the system without a corresponding benefit. Based on the conducted analysis, it can be concluded that the use of one optimally positioned sensor is sufficient for reliable temperature estimation, which opens up the possibility of simplifying the system and reducing implementation costs. However, the introduction of more sensors can be justified from the aspect of system reliability, because it enables the application of the "two out of three" logic, during which it is possible to detect and eliminate a defective sensor in the event of its failure.

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