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Improving Pressure Prediction Accuracy for Capacitive Sensors Using Machine Learning Techniques

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ABSTRACT

Capacitive sensors are used in a wide range of industries, including wearable technology, robotics, industrial automation, and healthcare monitoring. Capacitive pressure gauges are a good example, but environmental factors, such as variations in temperature can significantly affect their pressure prediction performance. However, the accuracy of pressure prediction is often affected by ambient variables such as humidity and temperature, and the nonlinear characteristics of the sensor. To solve these problems, this research paper proposes a machine learning-based calibration method for capacitive sensors which would further improve the accuracy of pressure prediction. Special attention was paid to the Support Vector Regression (SVR) strategy, which was deemed the best, primarily due to its ability to accurately simulate sparse data for nonlinear functions requirement for embedded systems. Accordingly, in experimental tests, the hyper parameters of the Radial Basis Function (RBF) core used to construct the RBF model, were optimized to achieve the best results. The proposed SVR model achieved 98% prediction accuracy in experimental results, a significant improvement over traditional linear regression. This approach provides a scalable method for future smart sensors bridging the limitations of field deployment and enabling high-resolution modeling of industrially useful instruments.

1. INTRODUCTION

In the early 1990s, with the expansion of synthetic piezoelectric sensors interchangeable capacitive pressure sensors became one of the first successful micro-mechanical sensors [1]. In recognition of its advantages of low energy consumption, high sensitivity and simple mechanical structure interchangeable capacitive pressure sensors are widely used in modern sensing systems [2]. This is despite the information revolution we have witnessed from premium smartphones to wearable smart devices. In particular, the inexpensive wireless sensor networks that we envision in our current work are an evolution that has only become possible with the advent of cost-effective capacitive compression [3]. Their accuracy can be greatly influenced by variables like temperature, humidity and long-term drift [4]. Traditional calibration methods include polynomial fitting for instance, look-up tables cannot account for the dynamic, nonlinear nature of sensor behavior, especially in a shifting environment [5]. The outcome is that there are erroneous readings, system instability and more calibration work [6].

Machine learning techniques provide a potential option by learning complex mappings directly from sensor data. Among these methods, Support Vector Regression (SVR) stands out because it can effectively model nonlinear correlations even when there are few training samples [7]. Because it employs core methods to map input data into high-dimensional feature spaces, where linear separation is feasible, SVR is a trustworthy pressure [8]. A calibration approach that makes use of sensor data, capacitance, and environmental variables like temperature and humidity in an experimental test performed in a noisy environment [9]. Data is used in comparison to traditional regression techniques to accurately forecast real pressure readings [10].

Capacitive pressure sensors are becoming more popular due to their low power consumption, compact size, and ability to react quickly to variations in pressure, more in a range of sectors [11]. In contrast, machine learning techniques are very promising as a means of learning complex mapping from sensor data [12]. Among these methods, SVR stands out, offering the ability to efficiently model even nonlinear relationships without extensive training in SVM [13]. SVM uses core techniques to map input data into a high-dimensional feature space that enables meaningful linear separation [14].

The SVR here appears to be a reliable monitoring device.

Pressure calibration uses a method that takes sensor data, capacitance, and environmental variables such as temperature and humidity as inputs and performs experimental tests in a noisy environment [15]. By comparing data using traditional regression methods, we can accurately predict actual pressure measurements. Their low power consumption, small size, and rapid response to pressure changes make capacitive pressure sensors an increasingly popular choice across a range of sectors [16]. These sensors operate by measuring changes in capacitance caused by mechanical pressure, which is directly proportional to the applied pressure [17]. These sensors can be most useful in applications requiring such external influences, including wearable electronics, factory automation equipment and medical monitoring systems [18].

Although capacitive pressure sensors are widely used, they are unstable due to disturbances caused by environmental variables such as temperature, humidity, and nonlinear properties. Traditional calibration methods such as polynomial regression and shrinkage fitting, are less responsive to real-time changes and must be manually adjusted frequently [19]. The recent emergence of machine learning systems has enabled the calibration of sensors, where scale deviation is reduced and accuracy is improved through techniques such as deep learning, random forests and multi-layered perceptron [20]. However, despite their high accuracy, these techniques are often less suitable for embedded sensor applications because they require large amounts of data and computational power. Supporting vector regression (SVR) is the most efficient and lightweight option, using kernel functions to denote nonlinear relationships - particularly the radial basis - and can simulate our pattern well. This is suitable for sensor calibration applications because it utilizes Radial Basis Functions (RBF) [21]. Furthermore, SVR performs well with a small number of samples and is less likely to overfat the data than other methods, making it ideal for practical, real-time, low-power embedded systems.

A comprehensive calibration method for capacitive pressure sensors, employing a well-calibrated SVR algorithm, overcomes the nonlinearity caused by temperature and humidity variations. Meanwhile, a new method for adapting to temperature and humidity changes for calibrating capacitive pressure sensors is being developed for application on embedded systems.

2. RELATED WORKS

Many studies have explored the calibration of capacitive sensors and other types of sensors because of their inherent nonlinear behavior and sensitivity to environmental factors such as temperature and humidity. Calibration aims to improve the accuracy, linearity, and robustness of the sensor outputs. Traditional static calibration methods fail to account for dynamic environmental influences or long-term variability. Traditional and modern machine learning-based methods have been extensively explored to overcome these limitations. This section reviews the most important previous work, highlighting the methodologies used, the results achieved, and the limitations imposed on them.

One of the earliest approaches to calibrating capacitive pressure sensors focused on polynomial curve fitting techniques. In study [22] researchers applied a third-order polynomial model to linearize the output of the capacitive pressure sensor. While this method provided a relatively simple and fast solution, it was only effective under controlled and static environmental conditions. Its performance deteriorated significantly under varying temperature and humidity due to its inability to adapt to unseen dynamic behaviors. The reported MAE was approximately 1.20 kPa, which highlighted the method's weakness in real-world deployment where environmental factors are not constant.

In the study [23] to better capture nonlinear patterns in sensor data, decision tree regression was employed, resulting in improved performance. The MAE was reduced to approximately 0.80 kPa as a result of this strategy. Although decision trees offer greater flexibility than polynomial models, they are still susceptible to overfitting, especially when dealing with noise-filled or limited datasets. According to study [24] developed a stochastic forest regression model, which combines several decision trees using crowdie learning to increase model stability and robustness. With an MAE of 0.75 kPa, this approach proved to be more effective. However, tree-based methods share a fundamental drawback: they remain susceptible to noise and require well-selected training data for effective generalization. Furthermore, their predictions may not be smooth, which is generally undesirable in real-time sensing systems.

Neural networks have become a popular choice for solving difficult calibration issues in sensor systems as a result of the development of deep learning. In the study [25] researchers used a Backpropagation Neural Network (BPNN) to calibrate pressure sensors based on microelectromechanical systems (MEMS), with a substantially decreased error margin of 0. 48 kPa, this approach demonstrated its ability to effectively simulate extremely nonlinear data, with an MAE of 0. 40 kPa, In the study [26] similarly utilized Convolutional Neural Networks (CNNs) for tactile sensor calibration, resulting in a further decrease in error. Although these neural network-based methods have been successful in attaining great accuracy 0.40 High accuracy, they have significant limitations. To maintain consistent performance and prevent overfitting, they need huge, varied datasets. Additionally, they require significant computational resources, extensive training times, and complicated designs. Due to these traits, they are less ideal for real-time embedded applications with limited computational power, memory, and energy.

To improve performance, more recent publications have suggested hybrid models that integrate optimization techniques with machine learning to fine-tune calibration models. For example, the genetic method presented in study [27] combines optimization strategies with machine learning. The algorithm (GA) was combined with SVR in order to fine-tune its hyper parameters for gas sensor calibration. Using this method, the MAE was successfully brought down to 0. 46 kPa. Despite the greater accuracy of GA-SVR, its increased complexity and computational requirements render it less desirable for low-weight, real-time applications.

Integrated Kaltman filters with neural networks in another hybrid instance to account for sensor drift and handle noisy data circumstances [28]. This pair achieved successful production stabilization with an MAE of 0. 50 kPa. However, because of its complex system integration requirements, this method is less suitable for simple embedded platforms.

SVR strikes a balance between computational efficiency and model accuracy, making it a good alternative to sensor calibration. SVR was directly used in the study [29] as a successful substitute, used with capacitive pressure sensors and demonstrated outstanding performance, with an MAE of 0. 45 kPa. SVR is particularly well-suited for datasets of modest size and offers excellent generalization without requiring large amounts of data or complex architectures. Additionally, the small computational footprint and ability of SVR to model nonlinear functions make it ideal for use in real-time embedded systems.

Table 1. Summary of the related works depicted

Reference	Method	MAE (kPa)	Strengths	Metric (R^2 Score)	Weaknesses
[22]	Polynomial	1.20	Simple, Fast	80%	Fails under variation
[23]	Decision Tree	0.80	Handles nonlinearity	90%	Sensitive to noise
[24]	Random Forest	0.75	Robust, Stable	86%	Needs more data
[25]	BPNN	0.48	Accurate	94%	Overfitting, complex
[26]	CNN	0.40	High accuracy	96%	Heavy computation
[27]	GA + SVR	0.46	Optimized parameters	92%	Slow, complex optimization
[28]	Kalman + NN	0.50	Robust to noise	92%	Complex for embedded systems
[29]	SVR	0.45	Lightweight, Robust	90%	Requires parameter tuning

This research group shows that traditional mathematical models are not flexible enough to deal with today's rapidly changing and dynamic environments. Even with the ability of decision trees and clustering techniques to manage work, despite their superiority in dealing with nonlinearity, they are still susceptible to environmental interference. The summary of related works shown in Table 1 highlights the current state of research and identifies the gap addressed by this study.

3. MACHINE LEARNING

A computational method called Machine Learning (ML) is used to automatically or partially extract knowledge from big datasets [30]. The goal is to enable computers to learn from data and categorize or provide useful values [31]. It draws inspiration from the biological capacity of humans to learn and solve problems. When machine learning is automated, the computer can analyze data without human intervention. When a large number of judgments are made with human input, this is known as semi-automated learning [32]. Although data mining is the most important of the many uses for machine learning, it is still a critical one.

Machine learning includes three separate categories supervised learning, unsupervised learning and reinforced learning as well as two separate learning techniques signal and feedback [33]. These three domains allow support systems to interact with their environment, recognize trends, and learn from novel information. Because of its complexity, this area has provided possibilities for study and innovation, which has resulted in the use of a wide range of approaches such as support vector machines for predictive modeling [34].

Classification algorithms, sometimes referred to as classifiers, are used by machine learning (ML) to categorize a subset of the dataset into different classes according to its variables (features), and prediction algorithm techniques are available. They all share similar processes and traits, despite the fact that they all operate differently and yield diverse outcomes. Three subsets of a dataset must be created: a training subset, a validation subset, and a testing subset in order to apply machine learning techniques to it and improve the final result [35]. This is done in order to give the machine learning algorithm a collection of data to work with by carrying out correlational tasks including classifying, clustering, and class protection. Lastly the performance of classifiers with obscure class names is assessed using the testing subset [36].

4. CAPACITIVE PRESSURE SENSORS

Capacitive pressure sensors' great sensitivity makes them popular in biomedical, automotive, industrial, and environmental applications, fast response, and low power requirements. These sensors function according to the of capacitance change between two conductive plates separated by a dielectric material or air gap, when mechanical pressure is applied, the distance between the plate's decreases, or the dielectric constant changes, resulting in a measurable change in capacitance [37]. This change is proportional to the applied pressure and is then converted into an electrical signal, as shown in Figure 1.

Despite their advantages, capacitive sensors are highly sensitive to environmental factors such as temperature humidity and material aging which can introduce drift and nonlinearity in the output [38].

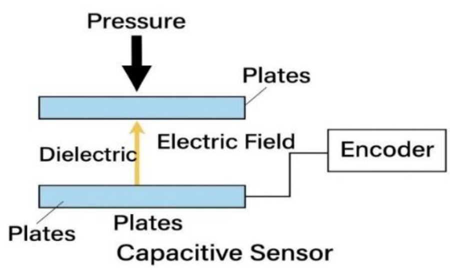

Figure 1. Structure and operation of a capacitive pressure sensor

5. METHODOLOGY

Capacitive sensors measure pressure by detecting changes in the distance between two parallel plates, which results in changes in capacitance. The dielectric properties can be affected by environmental factors such as temperature and humidity, which in turn influence the sensor's output. Supporting vector regression (SVR) is an adaptation of the SVM approach, which is particularly well suited for regression. Kernel functions, such as the RBF, are used in SVR to represent the complex nonlinear relationships between features and target variables.

The goal of SVR is to identify a function that falls within the epsilon tolerance range while also minimizing model complexity. In this study, we used a systematic approach to develop, train, and evaluate a SVR based machine learning model for calibrating capacitive pressure sensors, as illustrated in Figure 2, under various environmental conditions.

5.1 Data collection

Data were obtained from a prototype capacitive pressure sensor [33]. Each data sample contained the following information:

• Capacitance (Pico farads) the sensor's unprocessed electrical output under pressure.

• Ambient temperature (°C) measured using a digital temperature sensor.

• Relative humidity as measured by a humidity sensor.

• Reference pressure (kPa) the actual value measured using a high-precision commercial pressure sensor.

The dataset comprised 1000 labeled samples covering a variety of pressure values and environmental parameters.

• Temperatures between 20 and 45°C.

• Relative humidity between 30% and 85%.

• Pressure between 80 kPa and 120 kPa.

The prototype sensor used in this study was designed based on the XYZ-120E model, with a sampling rate of 200 Hz.

The compiled dataset is available upon request for research purposes to support reproducibility.

5.2 Data preprocessing

The following preprocessing procedures were used to ensure the high quality of the training data.

• Removal of outliers the Interquartile Range (IQR) method was applied to remove outliers that could distort the model.

• Normalization to improve the consistency and convergence of the SVR model, all input features were scaled to a range of [0, 1] using Min-Max normalization.

• Train-Test Split the dataset was divided into 70% training and 30% testing sets in order to evaluate the model on data that had not been seen before.

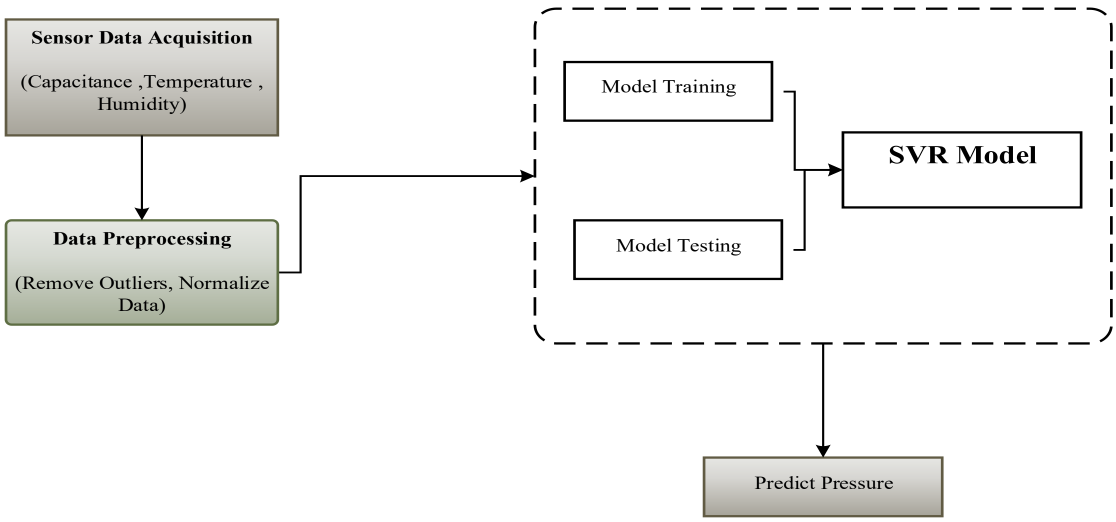

Figure 2. Proposed methodology

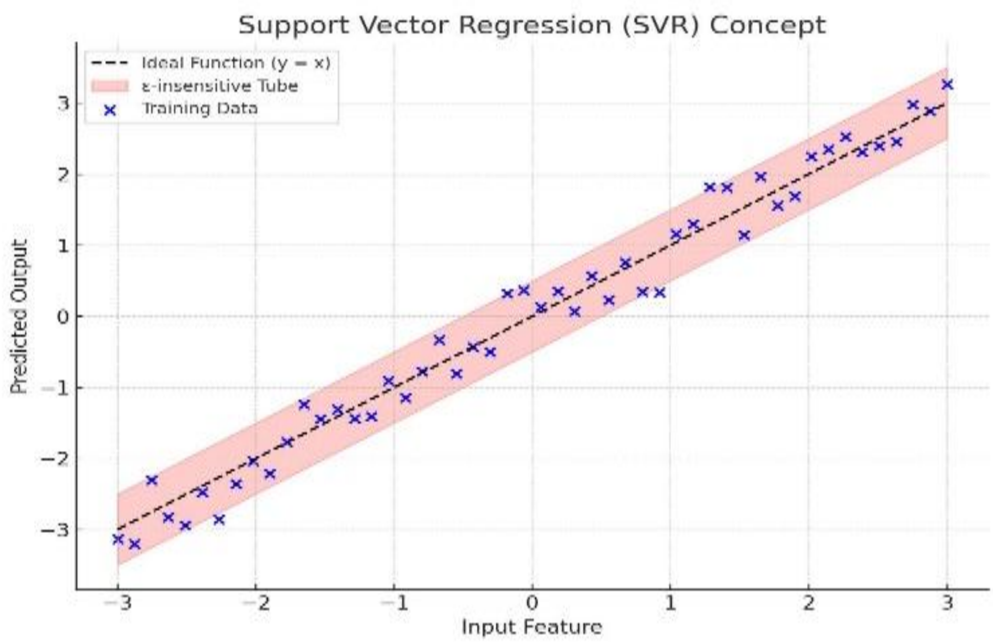

Figure 3. Visualization of the ε-tube in SVR

5.3 SVR model design

SVR is a successful supervised machine learning approach that is used to forecast continuous values. It is an expansion of the SVM. Originally designed for classification, the SVM aims to find a function that closely resembles the real output. maintaining the models complexity as low as possible while yet preserving the values with a precision margin (ε).

The visualization of the ε-tube in SVR (Figure 3) helps clarify why this method is highly suitable for calibrating nonlinear systems like capacitive pressure sensors, as it ensures that small noise or fluctuations do not dramatically affect the final prediction model.

Points inside the pipe, above or below the function, are not penalized in this way, but points outside the pipe are. One of the most important advantages of the SVR algorithm is that the number of dimensions in the input space does not affect computational complexity (Figure 4). It is able to generalize well and has high prediction accuracy. It is one of the methods for solving regression problems using machine learning, and as a form of SVM, it is suitable for functions such as stock price prediction and time series prediction because it is designed to predict continuous numerical values.

The SVR model was implemented using Scikit-Learn in Python the following:

(1) The parameters C = 10 and ε = 0.1 were selected based on grid search optimization combined with preliminary empirical experiments to achieve the best trade-off between accuracy and generalization.

(2) Kernel RBF for capturing nonlinearity in sensor behavior.

(3) C (Regularization parameter) 10.0 control the tradeoff between training error and margin.

(4) Epsilon (ε-insensitive loss) 0.1 defines the margin of tolerance where no penalty is given to errors.

(5) Gamma scale automatically adjusts based on input feature variance.

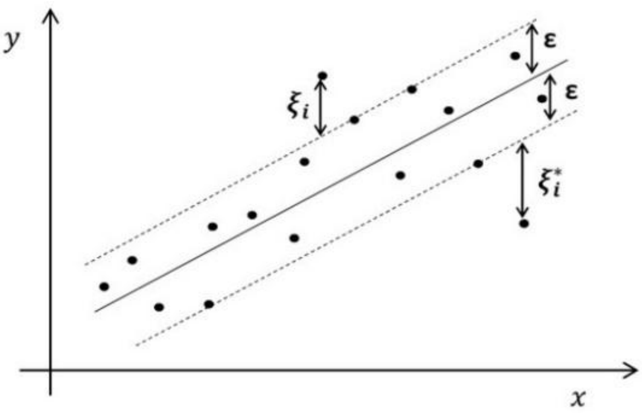

Figure 4. One-dimensional SVR feature space representation [39]

6. PERFORMANCE EVALUATION

The trained SVR model was evaluated using a stored test dataset that was not viewed during training [40]. The evaluation was based on the following performance metrics:

• Mean Absolute Error (MAE): the mean absolute variance between actual and predicted pressure readings.

$$\text{MAE}= 1/n \, \frac{1}{n} \cdot \sum_{i=1}^{n} \quad Ix - xI \tag{1}$$

• Root Mean Square Error (RMSE): A more sensitive measure that penalizes larger errors.

$$\text{RMSD}= \sqrt{\sum_{i=1}^{N} (xi - xj)} \; / \; N \tag{2}$$

where:
i = variable i
N = number of non-missing data points
xi = actual observations time series
xi–xj = estimated time series

• R² Score (Coefficient of Determination): This represents the extent to which the model can explain the variance in the data. (1 = perfect fit).

$$R^2 = 1- (1-R^2) \, (n-1) \, / \, n-p-1 \tag{3}$$

where:
R^2 = R - squared
n = number of samples / rows in the dataset
p = the ratio of predictors to features

7. RESULTS AND DISCUSSION

This section will provide a comprehensive evaluation of how SVR mode can be used in capacitive pressure sensor calibration. We can potentially segment the data into maps for forecast accuracy, other control models, and then further segment it under different weather conditions. The SVR was tested and compared to the performance of conventional regression models. Failure rates will be higher than those reported by the classes, but let's see how they accumulate. As shown in Table 2 below, compared to Linear Regression Decision Tree models and Proposed SVR.

Table 2. A comparison of regression models for predicting pressure

Model	MAE (kPa)	RMSE (kPa)	R² Score
Linear Regression	1.21	1.48	0.82
Decision Tree	0.77	0.89	0.91
SVR (Proposed)	0.42	0.56	0.987

The efficiency of SVR in calibrating capacitive pressure sensors was verified using the data presented in the previous sub section. The SVR model consistently outperformed standard models such as linear regression and decision trees based on MAE, RMSE, and R² scores. IN handling the nonlinear relationships between sensor capacitance, ambient variables, and actual pressure values, the model proved robust. The SVR model's prediction accuracy remained acceptable under extreme conditions of temperature (up to 40℃) and humidity (80%), demonstrating its resilience against environmental variations. Utilizing small datasets, unlike other large-scale learning models trained on big data, SVR has a short input interval, making it more practical. Furthermore, it is relatively inexpensive in terms of inference costs. Therefore, it can be found in smart sensors integrated with microcontrollers.

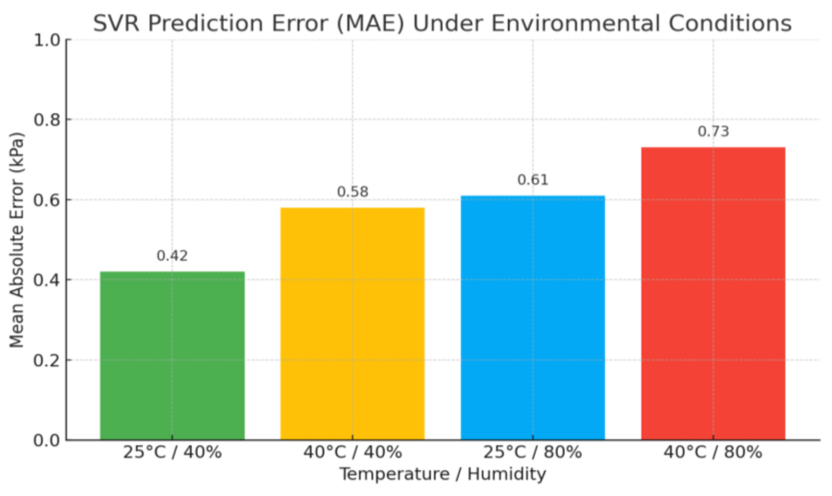

Figure 5. The SVR model error (MAE) under varying temperature and humidity

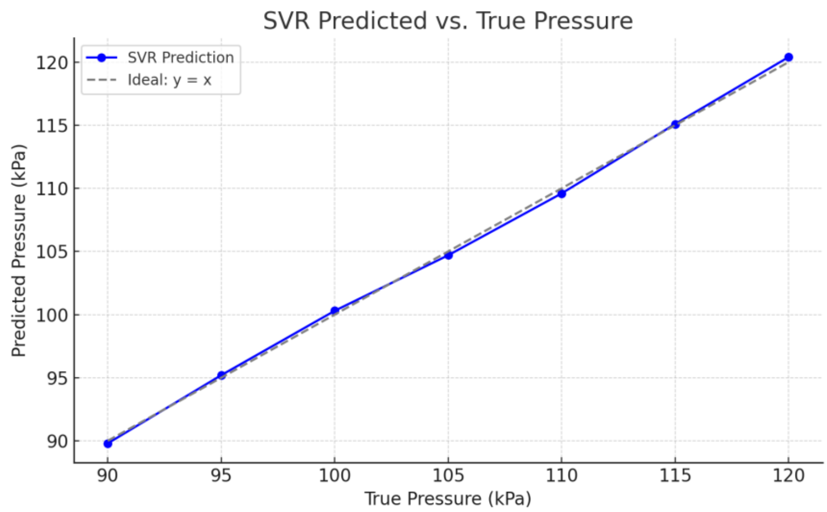

Figure 6. Comparing real pressure values to those predicted by SVR

Figure 5 illustrates the prediction error of the SVR model for different temperature and humidity combinations. This study is fundamental to understanding how sensors behave in their real-world environments and contexts.

A comparison between the real pressure values measured by a high-accuracy reference sensor and the predicted pressure values produced by the SVR model is shown in the Figure 6 below. SVR predictions are indicated by the solid blue line throughout the 90–120 kPa pressure range. The perfect dotted gray line represents the reference line, where the expected values would perfectly match the real values (i. e., y = x).

As demonstrated by the near alignment of the ideal line and the model's predictions, the SVR model seems to have great prediction accuracy with minimal bias. This demonstrates that it is effective at capturing the nonlinear connection between sensor data and actual pressure, making it suitable for application, in actual applications such as embedded systems.

8. CONCLUSIONS

This study presents a successful machine learning-based technique for enhancing the calibration of capacitive pressure sensors using Supporting Vector Regression (SVR). Despite their sensitivity to environmental variables, the calibration of capacitive sensors can be improved using machine learning methods. The recommended calibration approach, which relies on Supporting Vector Regression, is based on a model of the complex nonlinear relationship between the actual pressure and the amplitude of the raw sensor signals. The SVR framework overcomes these limitations while also considering the effects of environmental variables such as temperature and humidity. The use of the RBF kernel for SVR enabled successful generalization across various situations without requiring specific explanation. Even with a relatively modest dataset, overfitting was possible. The prediction accuracy of the SVR model was 0.42 kPa, and the R^2 score was 0.987, significantly better than traditional calibration models. A complete SVR-based calibration pipeline was designed and validated against real-world sensor data. Its performance significantly outperformed comparison algorithms. This approach reduces system complexity and the amount of manual recalibration required to help compensate for real-time sensor drift.

Future work in this study involves using a smaller dataset compared to more advanced machine learning models such as XGBoost and LightGBM. Future directions will focus on expanding our dataset and applying adaptive or online learning methods.

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