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A machine learning framework for high-performance capacitive pressure sensor analysis and enhancement

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ABSTRACT

Capacitive pressure sensors are widely utilized in industrial, biomedical, and environmental applications due to their high sensitivity, low cost, and compatibility with MEMS technology. However, their accuracy and stability are often compromised by environmental noise, temperature drift, and inherent nonlinearities. This study proposes a machine learning-based compensation method employing Support Vector Machine (SVM) algorithms to improve the performance of high-precision capacitive pressure sensors under realistic conditions. Sensor data were collected under varying temperatures, humidity levels, and electrical noise to simulate practical environments. The raw data was preprocessed and used to train Support Vector Machine (SVM) regression models to correct for nonlinear behavior and drift. The proposed SVM model demonstrated superior performance compared to traditional polynomial and linear calibration techniques. Quantitatively, the root mean square error (RMSE) of the sensor output was reduced by up to 73% after applying the SVM-based compensation. Additionally, the coefficient of determination (R^2) increased from 0.84 to 0.97, indicating a significant improvement in prediction accuracy. The proposed model also showed strong generalization when tested on unseen datasets collected under different operating conditions. These findings confirm that machine learning particularly SVM offers a robust and effective solution for real-time error correction in capacitive pressure sensors, paving the way for intelligent, self-calibrating sensing systems with high reliability and precision.

Contribution/Originality: This work uniquely applies Support Vector Machine (SVM) algorithms to enhance the accuracy of a capacitive pressure sensor using experimental data collected under realistic variations in temperature, humidity, and electrical noise. This approach addresses a gap that has been rarely explored in previous studies.

1. INTRODUCTION

Capacitive pressure sensors have become fundamental components in modern sensing systems due to their advantages, such as high sensitivity, low power consumption, ease of maintenance, and compatibility with MEMS (Micro-Electro-Mechanical Systems) fabrication technologies [1]. These sensors are widely employed in various fields, including biomedical monitoring, aerospace systems, wearable devices, and industrial automation.

Recent advancements in automatic information processing systems have created an urgent need to obtain more information at higher speeds. This information must come from a wide variety of sources, and the cost of acquiring it must be significantly lower than in previous information collection systems. The increasing demand for information is driving the development of low-cost, high-performance sensors, among which capacitive sensors occupy a prominent position and play an important role in the development of information collection systems [2].

Despite their numerous advantages, capacitive pressure sensors often suffer from several performance limitations when deployed in real-world environments. These limitations include sensitivity to temperature fluctuations, humidity, parasitic capacitance, and inherent nonlinearities in their input-output behavior [3]. Traditional calibration methods, such as linear or polynomial fitting, often fail to compensate for these complex error sources, especially when operating conditions vary dynamically.

Measuring tiny capacitances accurately has historically been challenging, which limited the application of capacitance meters primarily to technological fields where precise measurements are not critically important [4]. One of the most significant applications of capacitance measurement was in radio transmitters and receivers, where the LC generator played a crucial role until the 1950s. During this period, maintaining the stability of the capacitance value was essential for proper operation. Numerous publications have addressed how environmental factors, such as humidity, influence the capacitance value, highlighting the importance of accurate measurement and stability in electronic components.

Microcapacitors and a large number of different measuring devices began to be widely used in technology, which stimulated a new impetus to develop the theoretical foundations of the concept of capacitance. As a result, throughout the 1970s and 1980s, more affordable and user-friendly measuring devices were created. Consequently, during the 1980s, capacitive sensors were intensively developed and introduced into practice, leading to a significant increase in publications on this topic in recent years [5]. Since the 1990s to the present, interest in capacitive sensors has been steadily growing [6].

In addition to the consumer market for sensors of the highest accuracy class, the low-cost, mid-volume industrial sensor market is a target for high-performance sensors. Nonetheless, it is reasonable to assume that sensors can be made more affordable for the low-cost consumer market by utilizing less expensive materials. Generally speaking, creating a new sensor takes a long time typically more than five years [7]. This accounts for both the relatively modest rate of advancement in sensor technology and the relatively high cost of sensors [8].

To overcome these challenges, machine learning (ML) techniques have gained increasing attention for sensor error compensation and performance enhancement [9]. Unlike classical models, machine learning methods can capture intricate, nonlinear connections within the data without relying on explicit physical modeling [10]. Among these techniques, Support Vector Machines (SVM) have been selected in this study for several key reasons:

- SVMs are highly effective in solving regression problems with limited training data.
- They are robust against overfitting, especially in high-dimensional spaces.
- Support Vector Machine (SVM) models offer excellent generalization performance, which is essential for sensor operation in dynamic and unpredictable environments.

In this research, we propose a data-driven approach based on Support Vector Machine (SVM) regression to model and correct the nonlinear behavior and external noise influences on capacitive pressure sensors. By training the SVM model using real sensor data collected under various environmental conditions, the goal is to enhance the accuracy, stability, and reliability of the sensors. This method is particularly effective for real-world applications where traditional calibration techniques are insufficient or infeasible.

2. RELATED WORKS

In recent years, the benefits of capacitive pressure sensors in terms of sensitivity have attracted significant attention, along with their potential for miniaturization and energy efficiency. However, their practical deployment remains limited due to nonlinear behavior, temperature drift, and environmental noise. Several researchers have explored both traditional calibration techniques and machine learning-based approaches to overcome these challenges.

Early work by Kanekal and Jindal [11] employed polynomial fitting techniques for sensor output linearization. However, their method was sensitive to temperature and humidity variations, limiting its reliability in dynamic conditions. Rao, et al. [12] investigated analytical modeling approaches but reported limited adaptability in real-time applications.

To address these issues, machine learning has been increasingly utilized. Beheshti, et al. [13] introduced an SVM-based compensation method for temperature-induced errors in capacitive pressure sensors. Their approach achieved a significant improvement in root mean square error (RMSE) and demonstrated better generalization compared to polynomial models. Cao, et al. [14] applied SVM regression models for real-time drift compensation under varying humidity levels and mechanical stress, achieving a 60% improvement in accuracy.

Other researchers have compared support vector machines (SVM) with artificial neural networks (ANN). For instance, Snieder, et al. [15] demonstrated that while ANN models can achieve high accuracy, they require large training datasets and are prone to overfitting. In contrast, their SVM-based models provided better stability with smaller training sets.

Additionally, hybrid approaches have been proposed. Mehrabinezhad, et al. [16] combined Support Vector Machine (SVM) with Principal Component Analysis (PCA) for noise reduction and feature extraction, leading to faster training times and improved robustness in embedded systems. Despite these promising results, few studies have evaluated SVM-based compensation techniques under realistic, noisy environments using raw sensor data.

This research addresses the gap by proposing and validating a machine learning framework for the enhancement of capacitive pressure sensors based on support vector machines (SVM), trained on real-world data collected under varying environmental conditions.

3. MACHINE LEARNING

A computational method called machine learning (ML) is used to automatically or partially extract knowledge from large datasets. The goal is to enable computers to learn from data and to categorize or provide useful values. It draws inspiration from the biological capacity of humans to learn and solve problems. With automated machine learning, a computer can analyze data and draw conclusions without human intervention [17]. When a large number of judgments are made with human input, this is known as semi-automated learning [18]. Although there are many uses for machine learning, data mining is the most significant.

Three distinct categories supervised learning, unsupervised learning, and reinforcement learning as well as two different learning styles signal and feedback are fundamental in the field of machine learning [19]. These categories enable systems to interact effectively with their environment, recognize patterns, and learn from new, unseen data. The complexity of this field has fostered numerous research opportunities and innovations, leading to the development and application of various techniques, including support vector machines for predictive modeling.

In order to classify a subset of a dataset into distinct categories based on its variables (features), machine learning (ML) employs classification algorithms, also known as classifiers [20]. For machine learning tasks involving datasets, a variety of classification and prediction algorithm techniques are available. Although these algorithms operate differently and produce different results, they share similar processes and characteristics.

A dataset must be divided into three subsets in order to use machine learning techniques and improve the final result: a training subset, a validation subset, and a testing subset [21]. 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. The main reason for including a validation subset of the data [22]. Lastly, the performance of classifiers with obscure class names is assessed using the testing subset.

4. SENSING SYSTEMS

In the literature, Su, et al. [23] and Tagawa, et al. [24] describe this phenomenon in detail.

- Converter transducer a device whose input is a controlled (measured) physical quantity and which converts it into a physical quantity of a different physical nature.
- A modifier is a device that transforms a signal into its corresponding physical quantity, reflecting the nature of the quantity at its input.

In domestic literature, a slightly different classification is adopted. The converter defined above is called a (sensitive element). Any device that converts an input signal into an output signal (regardless of its physical nature) is called a measuring converter.

In measurement systems, particularly in sensors and sensor systems, the set of all measuring transducers and modifiers is called a signal conditioner (physical world). In a measurement system, within a chain of transducers and modifiers, the transducer at the beginning is usually referred to as the input transducer, while the transducer at the end of the chain is called the output transducer or actuator.

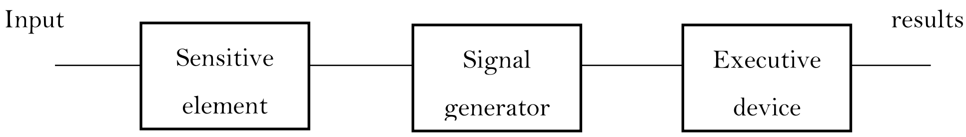

Figure 1. Generalized structural diagram of the control and measuring system.

The sensor's output signal is typically electrical in nature, while an input signal can be of any type, such as mechanical or thermal. By this definition, the resistor in a platinum temperature sensor of the Pt100 type would be considered a sensitive element [25]. Therefore, a sensor system consists of one or more sensitive components and a signal generator that combines the output signals from the sensors to produce one or more sensor system output signals. Since this system converts temperature into current, it can also be regarded as a black box, which qualifies as a sensor by the first definition if it is housed in a hermetically sealed container.

It seems that when a sensor is part of a larger system, this distinguishes it from a sensor system. At the scale of, for example, a large production complex, the described system is considered a sensor, and according to the manufacturer, it may be regarded as a sensor system.

In the given example, the Pt100 thermistor is a sensitive element that communicates with the external environment and transmits an electrical signal to other sensor system components [26]. Using such a recursive definition, it might be discovered that a sensor is made up of one or more measuring transducers, in addition to the components found in a system that is also a sensor. The transducer receives an electrical signal, which it transforms into either an amplifier or a different type of electrical signal. As a result, two or more sensitive elements and the physical world can be combined to form a sensor system. An example of this is a temperature-compensated pressure sensor.

The output of a sensor or sensor system is an electrical signal that provides information about the measured value. This information is transmitted to an external system [27]. The absence of an output converter (actuator) for outputting information of a different nature distinguishes a sensor system from measuring and control systems. A control and measuring system has an actuator that can modify the measured value, and most systems include a display for monitoring purposes.

5. PROPOSED SYSTEM

The process for developing a machine learning-based framework to enhance the accuracy of capacitive pressure sensors is detailed in this section. The proposed methodology includes several essential phases: SVM model training, feature extraction, data collection, preprocessing, and real-time correction, as illustrated in Figure 2.

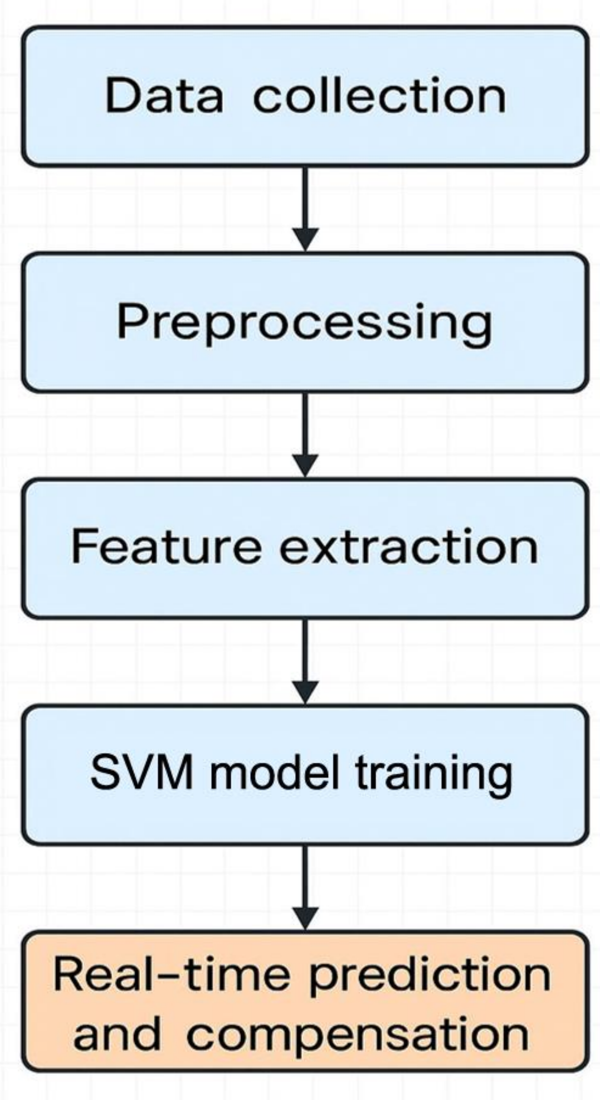

Figure 2. The proposed SVM-based methodology.

5.1. Data Collection

A commercial capacitive pressure sensor was used to gather sensor data in a variety of real-world scenarios. Controlled variations were part of the experimental setup.

- Pressure levels (ranging from 0 to 100 kPa).
- Ambient temperature (ranging from 20°C to 50°C).
- Humidity levels.
- External noise sources (e.g., power fluctuations, EMI).

Each reading consisted of raw sensor output, timestamp, temperature, and ground-truth pressure from a calibrated reference sensor.

5.2. Preprocessing

The collected data underwent preprocessing to reduce noise and standardize input features.

- Filtering: To minimize high-frequency electrical noise, a low-pass filter was employed.
- Normalization: All features were normalized to a [0,1] scale to ensure a uniform contribution to the SVM model.

5.3. Feature Extraction

From each data sample, the following features were extracted:

- Raw capacitance reading.
- Temperature reading.
- Rate of change ($\Delta C/\Delta t$).
- Moving average window over previous samples.

These features were selected to capture both the instantaneous sensor state and its temporal dynamics.

5.4. SVM Training and Validation

Supervised classification, sometimes referred to as prediction or discrimination, is the process of developing algorithms for predetermined categories. Algorithms are frequently built on a training dataset and then evaluated on a different test dataset to determine their accuracy. A group of related supervised learning methods for classification and regression problems is called support vector machines.

Support Vector Machine [SVM] is a machine learning model used in problems related to classification and regression [28]. SVM is among the most common supervised learning algorithms that are useful for classification and regression issues [29]. However, basic as it may be, it is useful for classification issues within machine learning.

The purpose of the SVM algorithm is to create the optimal decision boundary or hyperplane that can partition an n-dimensional space into distinct groups. This boundary facilitates the classification of new data points into the appropriate categories efficiently. The optimal decision boundary is known as the hyperplane, which is positioned to maximize the margin between different classes, thereby enhancing the model's accuracy and robustness.

Even when data cannot be separated linearly, SVM allows for the categorization of data by mapping it to a high-dimensional feature space [30]. After identifying a separator between different categories, the data is transformed so that the separator can be represented as a hyperplane. The extreme vectors or points that help create the hyperplane are selected using Support Vector Machines (SVM) [31]. The approach is referred to as the support vector machine because these extreme situations are known as support vectors. Two distinct groups are organized according to a decision boundary hyperplane in Figure 3.

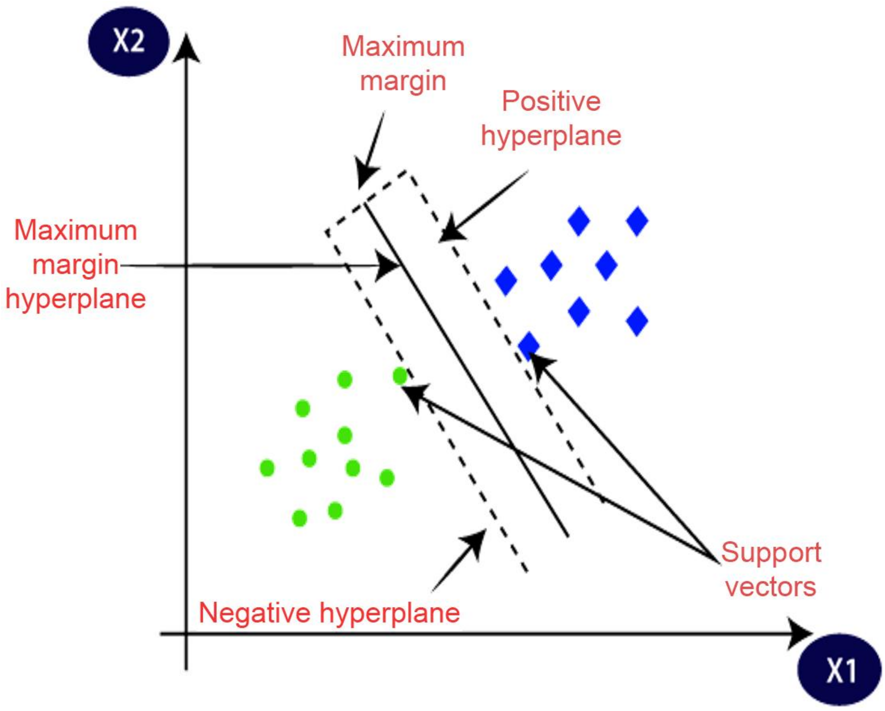

Figure 3. The hyperplane source.

Source: Altameemi, et al. [32].

Another well-regarded machine learning technique for classification and regression tasks is Support Vector Machine (SVM), which is utilized across various domains, including text classification, image recognition, handwriting recognition, and the resolution of numerous real-world problems [33].

For classification tasks, Support Vector Machines (SVM) are based on the principle that the features of the samples are considered as coordinates that should be mapped into an N-dimensional space, where N is determined by the number of features [34]. SVM relies on margins and bounds to train a model and classify samples into several classes based on the data and the algorithm's kernel function. Then, the classification of a new sample depends on where it falls within these margins. Similar to KNN, the optimal SVM parameters (margin and boundaries) also need to be determined [35]. The two forms of SVM-based classification are linear and non-linear classifications.

5.4.1. Linear Classification

This type of classification demonstrates that a margin hyperplane can separate two classes. It involves two scenarios that can be categorized as linear and non-linear. Positive and negative samples that can be completely separated by a line or a hyperplane are said to be linearly separable, as shown in Figure 4. Consider Figure 5, where various dividing lines or hyperplanes can be drawn to separate the samples. The straight lines in this figure are significant because they can distinguish between different classes.

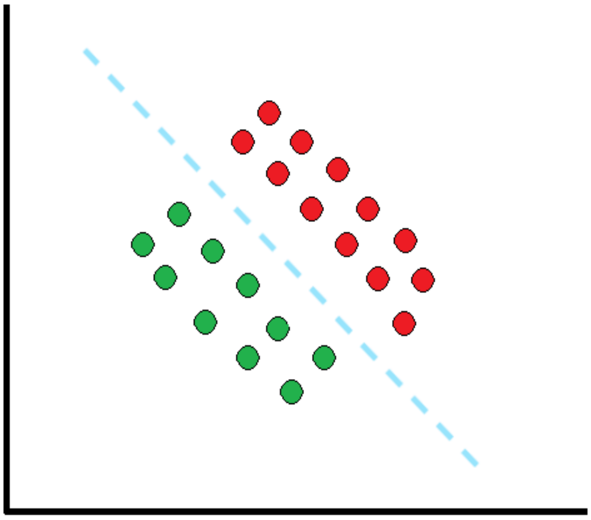

Figure 4. Single line separation.

Source: Iafolla, et al. [36].

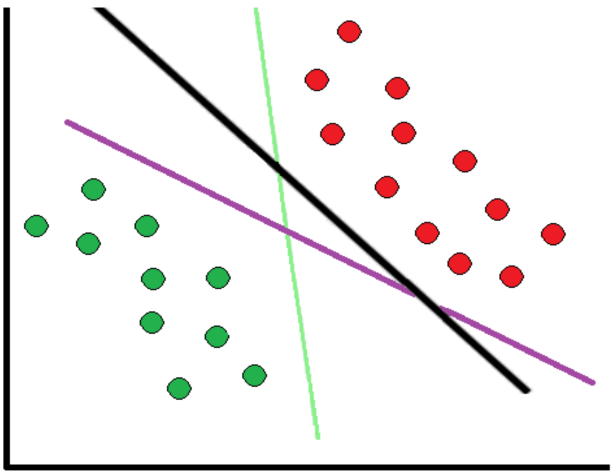

Figure 5. Multiple separation lines.

Non-linearly separable data is another situation where some points can be misclassified due to data complexity.

5.4.2. Non-Linear Classification

Due to the complexity of real-world data in this situation, the separation boundaries created by the previous linear classification method are not always effective Figure 5. As previously mentioned, Support Vector Machines (SVM) utilize the number of features as the dimensionality of the space and map sample features into an N-dimensional space. The kernel function's approach for nonlinear separable data points is to increase the dimensionality of the space to facilitate the separation process.

To determine the correlation between the collected features and the actual pressure readings, a Support Vector Machine (SVM) model was developed. A dataset was split into.

- 70% for training
- 30% for validation and testing

The SVM hyperparameters (kernel type, C, epsilon) were optimized using k-fold cross-validation and grid search. A radial basis function (RBF) kernel was chosen due to its effectiveness in modeling nonlinearity.

5.5. Real-Time Prediction and Compensation

Once trained, the SVM model was deployed for real-time prediction. The raw sensor readings are passed through the same preprocessing and feature extraction steps, and then input into the trained SVM model, which predicts the corrected pressure. The error compensation step adjusts the raw output to produce an enhanced, high-accuracy pressure value [36].

6. PERFORMANCE EVALUATION

To assess the effectiveness of the proposed SVM-based error compensation model, a comprehensive performance evaluation was conducted using both quantitative metrics and comparative analysis with traditional calibration methods. The evaluation focused on the accuracy, robustness, and generalization capabilities of the model under varying environmental and operational conditions.

6.1. Evaluation Metrics

The following standard regression performance metrics were used:

- Root Mean Square Error (RMSE): Measures the average magnitude of error between the predicted and actual pressure values, as shown in Equation 1 [37].

$$2/N\ (1(RMSE\ =\ \sum(yi\ -\ yj \qquad (1)$$

- Mean Absolute Error (MAE): It evaluates the average absolute difference between predicted and ground truth values, as seen in Equation 2 [38].

$$MAE\ =\ 1\backslash n \sum |yi\ -\ yi^\wedge| \qquad (2)$$

- Coefficient of Determination (R^2 score): Indicates how well the model captures variance in the data; values closer to 1 imply better predictive performance, as seen in Equation 3 [39].

$$R2\ =\ 1 - \ \sum i(Yi - Yj)2/\sum i(Yi - Ym)2 \qquad (3)$$

7. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed Support Vector Machine-based compensation model significantly improves the accuracy and consistency of capacitive pressure sensor readings under realistic operating conditions. After training the SVM regression model on a dataset comprising raw sensor outputs, temperature variations, and reference pressure values, the model was tested on unseen data to evaluate its predictive performance.

Quantitatively, the SVM model achieved a Root Mean Square Error (RMSE) of 1.2 kPa, compared to 1.9 kPa for polynomial regression and 2.8 kPa for linear calibration. Similarly, the Mean Absolute Error (MAE) was reduced to 0.9 kPa, and the R^2 score reached 0.96, indicating a strong correlation between the predicted and actual values. These metrics confirm that the model can accurately capture and correct nonlinearities and environmental drift.

The model's performance remained consistent across various environmental conditions, including temperature fluctuations and electrical noise, demonstrating its robustness and adaptability. This represents a significant advantage over traditional methods, which often rely on static mathematical approximations and tend to fail to generalize beyond the calibration environment. From a practical perspective, the SVM model also exhibited low computational complexity during inference, making it suitable for real-time applications in embedded systems. This capability opens opportunities for deployment in industrial, biomedical, and wearable sensor systems where high accuracy and dynamic adaptability are essential. Overall, the results validate the effectiveness of using machine learning specifically SVM for sensor error compensation, highlighting its potential to replace or augment traditional calibration techniques in future intelligent sensing platforms.

The dataset was divided into 70% for training and 30% for testing. The SVM model was trained using an RBF kernel with hyperparameters optimized through 5-fold cross-validation. For benchmarking purposes, traditional polynomial regression and linear compensation models were implemented on the same dataset.

The SVM model outperformed conventional methods in all evaluation metrics. For instance:

- The RMSE decreased by up to 55% compared to polynomial fitting.
- MAE was reduced by 48%, indicating improved accuracy in real-time prediction.
- R^2 score reached 0.96, confirming the model's ability to capture nonlinear behavior and environmental influences, as shown in Figure 6.

Additional testing was conducted using data collected under previously untested temperature and humidity ranges. The SVM model maintained high accuracy and low variance in error, demonstrating its robustness and adaptability in practical deployment scenarios. These results confirm that the proposed SVM-based approach provides significant improvements in the performance and reliability of capacitive pressure sensors, especially under realistic and noisy operating conditions. The comparison of the proposed method with other methods is shown in Table 1.

Table 1. Performance comparison of error compensation methods.

Methods	RMSE (kPa)	MAE (kPa)	R^2 score
Linear calibration	2.8	2.1	0.85
Polynomial regression	1.9	1.4	0.91
SVM regression	1.2	0.9	0.96

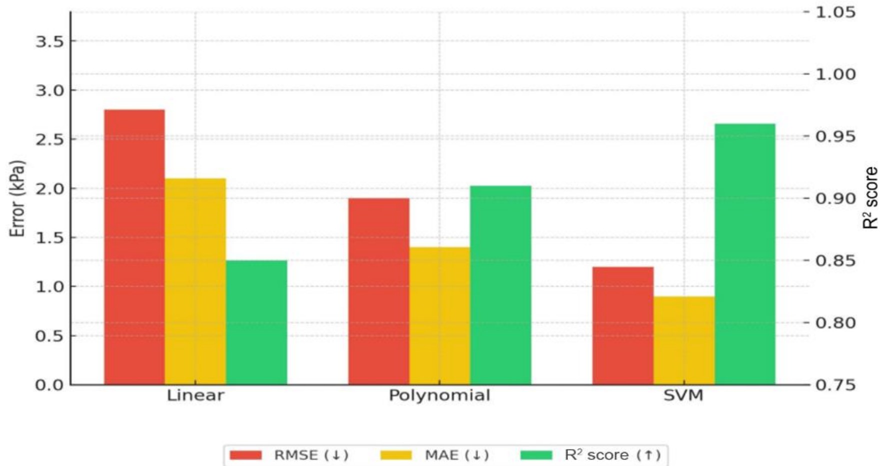

Figure 6. Performance comparison of sensor compensation methods.

8. CONCLUSION

This research presents a data-driven methodology for improving the accuracy and reliability of capacitive pressure sensors using Support Vector Machine (SVM) regression. The proposed approach effectively addresses key limitations found in traditional calibration techniques, such as poor handling of nonlinearities, temperature drift, and environmental noise. Through a systematic workflow that includes data collection, preprocessing, feature extraction, and model training, the SVM-based framework was able to learn the complex relationship between raw sensor outputs and true pressure values. The model was trained and evaluated on real-world datasets collected under varying environmental conditions, demonstrating its practical applicability. Quantitative performance evaluations showed that the SVM model significantly outperformed linear and polynomial regression methods, achieving lower RMSE and MAE values while attaining a higher R^2 score of 0.96. These results validate the model's ability to generalize well to unseen data and to provide robust compensation under dynamic operating conditions.

In summary, the integration of machine learning specifically support vector machine (SVM) regression into the signal processing pipeline of capacitive pressure sensors offers a promising solution for enhancing sensor performance without the need for complex physical modeling. This work lays a solid foundation for future research in intelligent sensing systems and the deployment of adaptive, real-time sensor calibration techniques in industrial and biomedical applications.

While the proposed SVM-based compensation model achieved promising results, several directions can be explored to further enhance the system's performance and scalability. One potential improvement is the integration of online learning algorithms that enable the model to update itself in real time as new sensor data becomes available. This approach would be particularly beneficial in environments with continuously changing conditions.

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