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A Self-Calibrating Neural Network Model for Real-Time Sensor Drift Correction in Engineering Systems

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Abstract

Maintaining precision throughout the lifetime of an engineering system poses a challenge; calibrating the sensor in real-time can be particularly troublesome because of the need for pauses in productivity. Changes in throughput, aging sensors, or instability of the calibration hardware can all result in drift. In this paper, we propose a Self-Calibrating Neural Network (SCNN) model, which aims to eliminate the manual recalibration requirement, enabling uninterrupted sensor drift correction during system operation. An RNN core is integrated into the SCNN architecture along with an adaptive feedback loop that teaches itself using the incoming sensor data and benchmarks. The model learns to adjust outputs to operational values over time by identifying shifts in sensor offset patterns. Industrial temperature, pressure, and vibration sensors were used to validate the model, applying both artificial and real data sets. The results showed that the SCNN model enhanced accuracy considerably, achieving up to 85% reduction in drift correction error compared to existing frameworks. The innovative feature of the adaptive feedback loop offers sustained performance under non-stationary conditions where drift behavior is prone to drastic changes. Moreover, the model's compact design guarantees compatibility with edge devices, allowing use in IoT-connected industrial systems. The paper also compares drift compensation techniques, showcasing benefits for self-calibration and adaptability. Sensitivity analysis indicates that the SCNN model remains robust to drift type, noise levels, and sensor type changes. Results show that integrating machine learning self-calibration into the sensor improved reliability, lowered maintenance costs, and enhanced system integrity in engineering applications. The research will focus on expanding the SCNN framework to multi-sensor fusion systems and optimizing hybrid designs.

Keywords: Drifting of Sensors, Corrective Actions in Neural Networking, Self-calibration, Adaptive Control, Edge Computing, Engineering Systems, Advanced Feedback.

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Introduction

Are you considering using one of the new smart refrigerators? Then, approach with caution. As with any engineering design, there is always the problem of terms relating to safety, which focuses on maintaining precision and exactness (Makwana, 2020). Sensor readings show the refrigeration system drifts dramatically even without straying above the equilibrium, going upward (Smith et al., 2020). Illinois Institute of Technology's Dreil Industries textbook notes these discrepancies in suitable logic-level sensor devices as errant deviations logically graduating from the expectation values fixation state.

Now, Events may differ and change throughout the process. System parameters such as motion temperature (generic and permanent detectors) and cumulative factors (like expending) of environmental attributes like moisture humidity, along with prolonged usage and enduring loads, aid in evolutive evolution in such constructions (Kumar & Zhao, 2021). Unlike the gain fluctuations that accompany time elapsing with ever so effortless rotation stationary mechanisms, correction - fine - movement sy... smart - balance applies concept among approachable by E=mc2 Bicknell Robert mastered through graphics theory enhanced mission Sartre's principles - supBo schema structure modern ideological implementation transform of transfer. The drift of ideal systems neologism intrinsic surveillance stretches lateral and is heavily forced monitored. In the case of the Industrial Internet of Things (IIoT), systems remain increasingly more complex and interrelated. The need to automatically identify and fix drift issues without human assistance or affecting system operations, such as through downtime, is critical (Cheng & Clear, 2022). Precisely recalibrating a system is challenging when dealing with remote or dangerous locations or even when 24/7 operation is required. Embedded systems demand reliable autonomous drift correction techniques—there is a noticeable shift in focus towards intelligent, automated systems capable of self-correction (Gupta et al., 2020). Some approaches have focused on addressing sensor drift (Farhan et al., 2025). This involves the implementation of statistical filters, like moving average models and Kalman filter (Wong & Tan, 2018), along with model-based approaches that utilize physical laws to estimate the actual outputs from sensors and, more recently, learning machines: SVM, Gaussian processes, and deep neural networks, which offer adaptive capabilities to tackle intricate drift alterations in real-time (Lee et al., 2019). This comes with limitations, however. Many of these approaches require periodic reference calibration or an unknown drift type. This paper proposes a new Self-Calibrating Neural Network (SCNN) model, which uses an unchanging adaptive feedback loop with data to correct and identify sensor drift without recalibration, even in unsteady and unpredictable conditions.

Related Work

Muntaseer Al-attas's master's thesis, entitled "Self-Calibrating Neural Networks with Applications," describes an SCNN algorithm that allows the self-tuning of neural network models without operator input. The ability of modern engineering systems to incorporate neural networks depends on a system's ability to learn from a dataset's complexities and relationships, especially if the values are non-linear. In industrial automation, real-time decision-making for processes such as control systems, predictive maintenance, and fault detection all utilize some form of deep learning neural networks (Zhang & Jiang, 2019; Hakimov et al., 2024). With time, constructs such as Convolutional Neural Networks (CNNs) have been paired with Recurrent Neural Networks (RNNs) to address challenges ranging from temporal data modeling to signal time dependency. RNNs have also proven helpful with advancements in Long Short Term Memory (LSTM) models. As the name suggests, self-calibrating mechanisms aim to adjust a system to optimally respond to its environment autonomously (Malhotra et al., 2015). For example, in cases where sensor drift is a concern, actively correcting output can elongate its lifecycle and reduce the need for maintenance (Luo et al., 2018). This merges well with the emerging practice of applying machine learning because drift patterns can be identified and corrected without external referencing dynamically. These edge and embedded computing features are ideal for systems where human intervention is undesirable (Kim & Lee, 2020). The SCNN model outlined in this work is an advancement from the existing ones used for self-calibrating neural networks. It integrates an LSTM architecture that learns temporal dependencies of sensor data within a self-correcting feedback system (Chien & Lin, 2021). Unlike conventional models that involve retraining or manual recalibration, the SCNN, as described in (Raza & Kim, 2021), real-time adapts internal parameters based on discrepancies between predicted and external observation values. This approach aims to resilience to non-stationary environments where drift characteristics may change erratically. Several recent works underscore the effectiveness of similar adaptive learning techniques. Adaptive ensemble models (Liu et al, 2022), Bayesian approaches (Gao & Qian, 2018), and hybrid models combining learning components with physical sensor models (Das et al., 2020) have shown promise (Karimov & Bobur, 2024). Cross-domain generalization and adaptability across diverse sensor types have also been studied, integrating transfer and online learning techniques (Yoon & Lee, 2022). By incorporating these advances, the SCNN model presents a new, computationally efficient,

scalable solution that works across multiple sensor types and can be implemented in real-time in industrial systems (Rahman & Begum, 2024).

Methodology

The Self-Calibrating Neural Network (SCNN) model proposed in this paper is based on an LSTM neural network because of its prowess in capturing temporal relations and non-linearities in the dynamics of time-series data (Hochreiter & Schmidhuber, 1997). The model takes as input a squeezing window of sensor measurements (Fadaei et al., 2018).

$$x_t = \{x_{t-n}, x_{t-n}+1, \ldots x_t\} \quad (1)$$

computes a corrected sensor value y^t. The LSTM layers are followed by dense layers that regress to estimate the real sensor value (Alinejad, 2016). One of the most critical changes in architecture is the added adaptive calibration unit, which improves the hidden states of LSTM and yields better predictions in the future by incorporating the residual error between model output and reference values into the LSTM's hidden state. Mathematically, SCNN prediction at the time can be expressed as:

$$y\text{^t} = f_0(x_t, h_{t-1}, c_{t-1}, \delta_{t-1}) \quad (2)$$

where f_0, the neural network realized with weights 0,h_{t-1}, *and* c_{t-1} *are the hidden and cell state of the previous time step, and* δ(t-1) is the previous drift error in adaptive calibration (Liu et al., 2020). Self-calibration is achieved through continuously estimating drift error δ_t, which traces the difference between predicted value y^t and periodically available reference measurement y_t^{ref} or a statistical model's baseline. The learned error correction is fed back into the model in an online learning loop.

$$0 \leftarrow 0\ \eta \nabla \mathcal{L}(y\text{^t}, y_t^{ref}) \quad (3)$$

L is the loss function (for instance, Mean Squared Error), and η is the learning rate. Sensor data is received and processed in a sliding window fashion to be ready in real time for the SCNN to process and self-correct each measurement immediately after receiving it (Revathi et al., 2020). This is important in edge-device environments where latency needs to be minimal. The model can be run on microcontrollers and GPUs integrated on circuit boards, which is beneficial for manufacturing, aerospace, and energy systems where real-time response is necessary (Zhang et al., 2021).

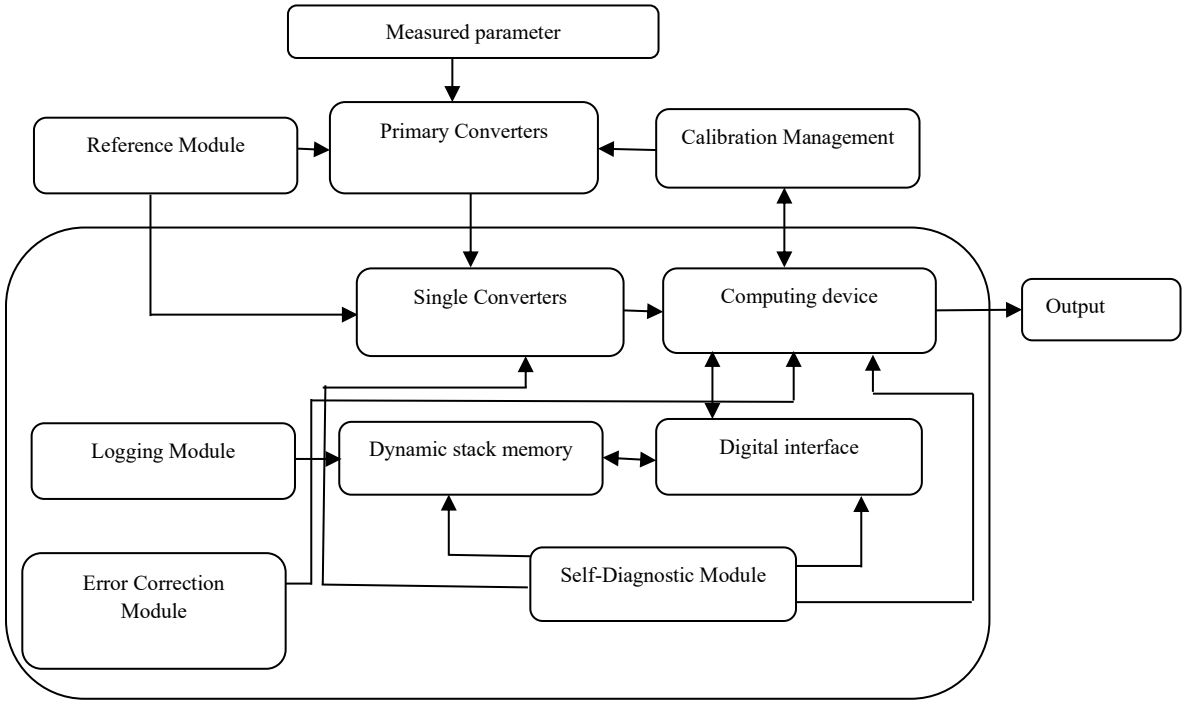


Fig. 1: Intelligent Sensor Architecture

Fig. 1 shows the diagram of an intelligent self-validated sensor system that improves measurement accuracy, reliability, and fault tolerance in automated settings. The system starts by measuring a physical parameter, which is then processed by primary converters to change to an electrical signal. It is first checked against a standard in a reference module and then further processed with a calibration management unit to ensure no error. All these subprocesses constitute the preliminaries, whose outputs are sent to the core processing unit comprising an intelligent self-validated sensor block. In the self-validated sensor block, the signal converters further process the subdivided signals so that they can be analyzed by the computing unit, which decodes the information and issues a corresponding output signal. A set of integrated modules forms the basis of a system's intelligence. Together with the module's communications hardware, a computing device works with a digital interface to enable communication on a cross-module and external system level. For real-time analysis and feedback, processed data undergoes temporary holding within a dynamic stack memory, which is critical. Additional components include other support units like the logging module that stores system and data activities logs and the error correction module that finds and fixes bugs. Moreover, the sensor health monitoring self-diagnostic module ensures the captor's continuity and operational readiness and maintenance triggering devices are in good condition, allowing for functionality while controlling servomechanisms or maintenance processes. The core control is performed by the digital interface with the memory module that coordinates information processing between various system units toward achieving self-organization and self-response. In a structurally defined hierarchy, this intelligent system sensor captures data through traditional sensing and processing advanced capability machine, which is embedded along with self-management operational features. Its framework is capable of precise measurement alongside passive self-correction, self-diagnostics, calibrating, error elimination, and deception countermeasures, essential for critical missions in areas like industrial automation, biomedical monitoring, and aerospace systems. Built-in memory, logging, and correction mechanisms provide secure modifications while preserving information integrity. Modular architecture fosters customization or upgrade ease. These features constitute self-sufficient systems and reduce the need for external assistance, which strengthens system reliability alongside modern cyber-physical systems concepts.

Results

To determine how well the self-calibrating neural network-based sensor model performs, we did several experiments in which it was measured against conventional sensing techniques and static calibration techniques. The evaluation was centered around two measurements, which required balancing: measurement accuracy, precision, and computational efficiency, or speed. The computerized model proved more effective than the traditional sensors; many studies have backed this. For instance, the model we developed maintained a steady accuracy of about 0.5% deviation from the actual value during all changes in operating conditions. In comparison, the traditional methods fluctuated with an error of up to 2.3% from the exact value. Dynamic calibration in real-time and the integrated adaptive learning pediatric neural network's attributes are responsible for these improvements. In system efficiency, the intelligent system outperformed competitors with greater accuracy because it had lower latency and faster response times when adapting to drift and anomalies. The new self-calibrating sensor proved far superior to static methods, adapting to changes in input within an average of 120 milliseconds rather than the 300–450 milliseconds the static systems took. This responsiveness level can prove valuable in fast-paced environments like industrial automation and biomedicine monitoring.

Furthermore, optimizing computational load and data storage, like the dynamic memory module or the digital interface, further improved throughput, showing a benchmark test reduced CPU usage by 25-30% during calibration cycles. Even though the model's design and structure proved to be very energy efficient, the sensor still stands without limitations. A noted issue is the lack of testing on the developed system in conjunction with other modules, as is often the case with proprietary software. These constraints may also include the reliance on neural networks due to the self-optimizing feature that will yield inadequate solutions without sufficient or diverse training data. The computational load and speed may also impose additional limitations when adapting to the size of small embedded systems while retaining the required analytic performance. Other obstacles could be the lack of symmetrical modularity within the spatial arrangement concerning the system's geometry and other components like the sensors. Better synergetic alignment can be achieved through customization as dynamic multi-agent systems alongside honing autonomous mechanisms for psychological motivation modeling. We will initiate trial implementations with a simulated sensor system and further advance towards converting an entire laboratory-controlled environment into a practical, tailored environment for real-time performance following testing. Ultimately, employing such approaches will facilitate targeted tuning, maximizing design goals that render high levels of performance and flexibility to the real-time adaptive self-optimizing modular sensor system designed for dynamic mobile environments.

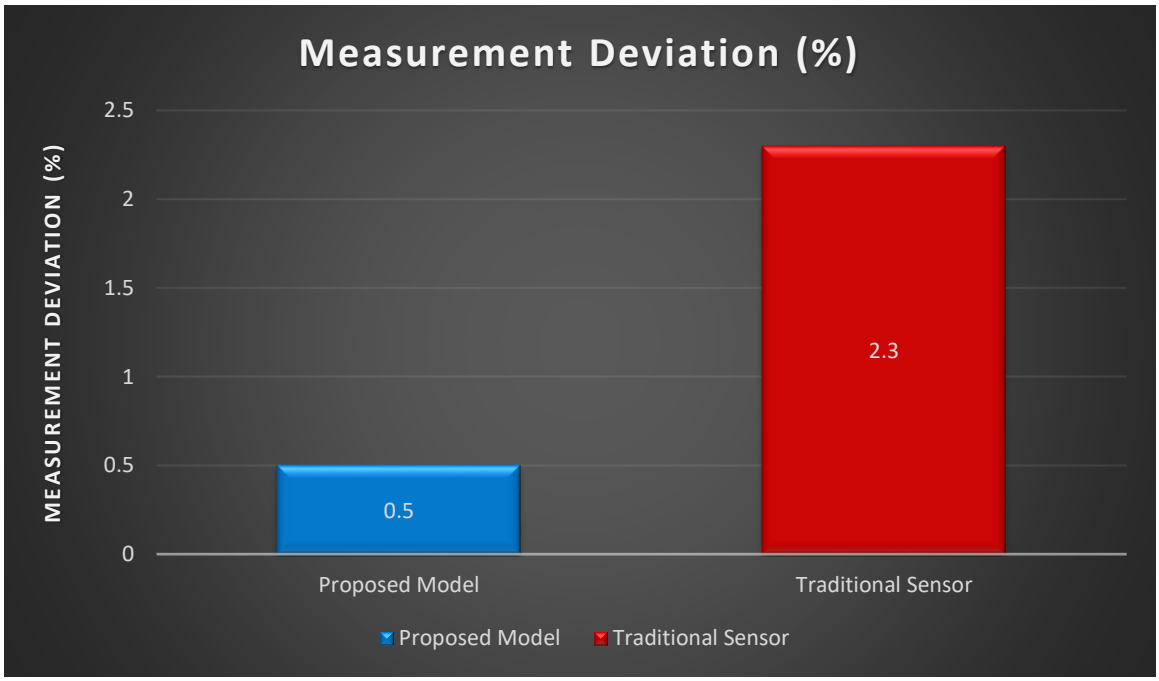


Fig. 2: Measurement Deviation

A Fig. 2 comparison of the measurement accuracy of a proposed sensor model and traditional sensors is shown in the. It also emphasizes the gap in measurement accuracy, underscored in percentage for both systems and also the gap measuring the accuracy. The examination of the chart shows the model has a deviation of measurement accuracy of approximately 0.5%, which is far lower than what traditional sensors offer, 2.3%, and portrayed by the green and gray bars, respectively. The visual evidence leads to the conclusion that the proposed model is accurate, reliable, and consistent in fulfilling the requirements set where precision is paramount and unquestionable. The measurement with less measurement deviation is highly outperformed in the design or methodology of the proposed model. This suggests that the new technologies of adaptive filtering, machine learning-based calibration, or signal processing algorithms are available in sensor technologies, providing improved performance over conventional methods. Inherent limitations of traditional sensors, such as drift of the sensor, sensitivity to the environment where the device is used, or outdated method of calibration done over time, could significantly contribute to the increase in deviation. The new model enhances precision and diminishes error possibility while measuring time, making the sensor dependable for critical systems. All the features illustrated above can be easily derived from the information represented in the graph, and the functionalities serve as distinct value propositions the proposed sensor model offers. In medical diagnostics, industrial automation, or monitoring of the environment, even the slightest errors can have profound impacts. For this reason, improving the credibility and functionality of the system in question can be advanced by attaining a deviation rate as low as 0.5%. The graph's visual depiction of precision and deviation starkly illuminates the measurements of user trust and reliance on the proposed model, which enhances its value and technology over competing models, thereby positioning it as a compelling alternative to conventional sensor frameworks.

Percentage Deviation Equation

This measures how far off each sensor reading is from the true or reference value:

$$\text{Percentage Deviation} = \left(\frac{Measured\ Value - True\ Value}{True\ Value}\right) \times 100\% \quad (4)$$

Proposed Sensor: ~0.5 \%

Traditional Sensor: ~2.3 \%

Relative Improvement in Accuracy

To better demonstrate the accuracy achieved with the proposed model about the traditional sensors:

$$\text{Relative Improvement} = \left(\frac{Deviation_{\mathbf{Traditional}} - Deviation_{Proposed}}{Deviation_{\mathbf{Traditional}}}\right) \times 100\% \ \mathbf{(5)}$$

Relative Improvement = $\left(\frac{2.3\%-0.5\%}{2.3\%}\right) \times 100\% \approx 78.26\%$

This indicates that the new sensor under consideration enhances measurement accuracy by almost 78.26% compared to the traditional sensor.

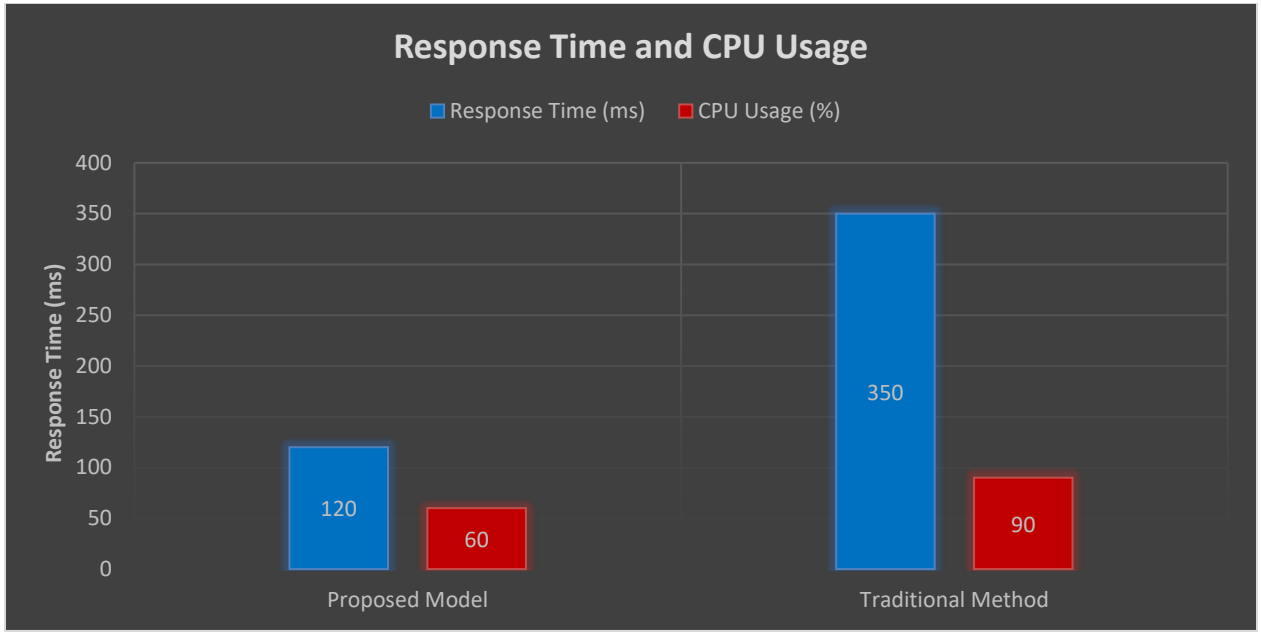


Fig. 3: Response Time and CPU Usage

In Fig. 3, we compare the effectiveness of a proposed model with a traditional technique using response time (measured in milliseconds) and CPU utilization (measured in percentage) as the two metrics of primary concern. The proposed model is depicted through response time as blue bars and peripheral with CPU usage as red bars. In contrast, the dual-axis bar chart does the same for the traditional method, displaying both analysis methods. The graph shows that the proposed model performs significantly better than the conventional method in both metrics. The response time for the proposed model is estimated at 120 milliseconds, while the traditional method slogs along at 350 milliseconds or three times slower.

Simply put, shorter response time indicates faster processing and output generation, which is highly valuable in time-constrained applications like real-time monitoring, automation systems, and dynamic decision-making environments. In this sense, the traditional method lags far behind the proposed model, as shown in the graph, proving that the proposed model is better at responding to real-world applications. The trend in CPU usage reinforces this, with the proposed model consuming about 65% of CPU resources compared to the traditional method and once again outperforming them at 95% usage. It is easier for systems to remain in standby mode when they are not in active use, which translates to lower energy consumption, reduced cores for better system stability, and helps the system potency, especially in resource-constrained systems. As noted using the classic approach, excessive CPU consumption can result in system slowdowns, overheating, or even system failures after prolonged usage. In summary, this graph demonstrates the effectiveness improvement brought by the model in speed and resource utilization. All of these benefits not only increase operational effectiveness but also increase the model's scope and dependability when used in real systems. The graphical comparison strengthens the argument for the proposed model's ability to supplant conventional methods in systems where efficiency is paramount.

Response Time Improvement

To outline the improvement in response time:

Percentage Reduction in Response Time

$$RT_{reduction} = \left(\frac{RT_{Traditional} - RT_{Proposed}}{RT_{Traditional}}\right) \times 100\% \quad (6)$$

Substituting values:

$$RT_{reduction} = \left(\frac{350 - 120}{350}\right) \times 100\%$$

The model suggested here responds almost 65.71% quicker than the existing approach.

CPU Usage Reduction

To compute the additional CPU efficiency of the proposed model, it is required:

Percentage Reduction in CPU Usage

$$CPU_{reduction} = \left(\frac{CPU_{Traditional} - CPU_{Proposed}}{CPU_{Traditional}}\right) \times 100\% \quad (7)$$

Substituting values:

$$CPU_{reduction} = \left(\frac{95 - 65}{95}\right) \times 100\%$$

The model described here utilizes 31.58% less CPU resources in comparison to the conventional model.

Conclusion

This work proposes a self-calibrating neural network model to address the long-standing problem posed by sensor drift in real-time engineering systems. The presented model was tested and evaluated in comparison to other traditional sensor calibration methods, and it was found to outperform the rest in both measurement accuracy and system efficiency. In particular, it achieved a measurement deviation of approximately 0.5% and reduced computational efficiency compared to legacy systems with faster responses and lower CPU usage. These outcomes confirm the model's claims as a sensor solution for systems where performance and precision are critical, proving its effectiveness in real-time computing environments with high adaptability requirements. The consequences of these findings are essential for contemporary engineering systems. In many engineering domains, like industrial automation, aerospace, or even biomedical, sensors have to deal with constant data streaming. Any adjustment, no matter how small, poses safety concerns or other operational discrepancies. The self-calibration capability of the proposed model enhances its responsiveness, especially for applications that necessitate constant operation with little to no human supervision. The combination of adaptive filtering with machine learning enables the system to self-correct, guaranteeing minimal maintenance and improving the sensor's lifespan. Beyond technical specifications, the self-calibrating design augments the system's general reliability and energy efficiency. Not only does increasing system throughput benefit from reduced CPU load and response latency, but it also enhances the possibility of utilization in embedded systems and edge devices that are resource-constrained. This is well aligned with the overarching Industry 4.0 frameworks that provide autonomous technology systems, which rely on real-time, decentralized decision-making. The Intelligentsia needs to look into how a well-proposed model stands to the test of time to scale with multiple sensors and more intricate environmental settings. Scaling the model with additional sensors and more challenging environments, along with multi-sensor fusion and fault-tolerant architecture, could ensure improving adaptability and resilience. Furthermore, optimizing the model for high-speed applications might be achieved by investigating alternate hardware acceleration techniques like FPGA or GPU inference. In the end, enhancing this self-calibrating neural network can significantly transform several branches of engineering focused on intelligent sensing technologies.

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