Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4, 2976-2989
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i4.6703

Smart wearable devices for anxiety regulation in pet dogs: Integrating deep learning with thin-film materials

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Abstract: The safety and emotional well-being of companion animals, particularly pet dogs, have become significant concerns in recent years. Anxiety is a common issue among pet dogs, manifesting in behaviors such as excessive barking, pacing, trembling, and even destructive actions. These behaviors can profoundly affect both the dog's well-being and its owner's peace of mind. This research proposes a novel system that integrates deep learning (DL) algorithms with smart thin-film materials to monitor and regulate anxiety in dogs through a smart wearable solution. To analyze and detect anxiety regulation in pet dogs, a Tangent Search-driven Stacked Convolutional Neural Network (TS-StackedCNN) model is applied. Data is sorted into three levels of anxiety severity, where Level 1 is the lowest anxiety, Level 2 is moderate anxiety, and Level 3 is high anxiety. In the preparation of raw sensor data, a Gabor filter is applied during pre-processing to filter out noise and outliers so only the relevant data can be analyzed. Feature extraction was performed using Linear Discriminant Analysis (LDA) to find important features distinguishing each anxiety level. The TS-Stacked CNN model was able to reach a high level of accuracy after processing these features, where Level 1 had precision equal to 0.950, recall equal to 0.949, and F1-score equal to 0.948; Level 2 had precision equal to 0.946, recall equal to 0.889, and F1-score equal to 0.919; and Level 3 had precision equal to 0.864, recall equal to 0.868, and F1-score equal to 0.865. This interdisciplinary approach advances both animal behavioral science and functional smart materials, paving the way for real-world applications in pet care, veterinary monitoring, and stress intervention technologies.

Keywords: *Anxiety detection, Anxiety regulation, Functional smart materials, Pet dogs, Tangent search-driven stacked convolutional neural network (TS-StackedCNN), Thin-film material systems.*

1. Introduction

Animal anxiety is a stress-related emotional state triggered by fear, new experiences, or environmental changes, resulting in signs like restlessness, excessive vocalization, hiding, shaking, destructive behavior, and changes in appetite and grooming [1]. Animal anxiety regulations are legal frameworks designed to ensure the psychological, mental, and emotional well-being of animals, preventing them from experiencing excessive stress, anxiety, or distress, similar to human anxiety [2]. Animal anxiety regulations exist as part of the wider span that is animal welfare legislation, but there is animal anxiety legislation that governs important areas such as life conditions, transport, housing, veterinary care, handling, etc. [3]. The regulations address animal anxiety as a condition, addressing excessive vocalization, destructive behavior, and restlessness. Psychologists view it as a responsibility to encourage anxiety reduction through behavioral modification techniques, similar to teaching people methods to reduce their anxiety [4]. In businesses, like an animal zoo, research laboratory, animal farm or human domestic, regulatory bodies see acceptable policies, plans and practices utilizing various

History: Received: 25 February 2025; Revised: 9 April 2025; Accepted: 14 April 2025; Published: 29 April 2025
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enrichment strategies, adequate space and positive reinforcement to achieve reductions in the psychological suffering of animals [5].

Veterinarians and pet owners are becoming increasingly concerned about companion animals' emotional health and overall well-being, particularly pet dogs. Anxiety is one of the wide variety of animal behavioral health concerns that are frequent in dogs and it can be caused by separation, loud noises, unusual environments, and changes in habit [6]. One popular category of complementary and alternative therapies that make use of interactions with a trained dog is called canine-assisted interactions (CAIs). CAIs, like all other animal-assisted interactions (AAIs), aim to enhance the quality of life of human participants as measured by certain clinical endpoints (e.g., blood pressure, cortisol, etc.) [7]. Smart wearable devices, such as collars, harnesses, or vests, are advanced sensors that monitor and enhance the health, behavior, and well-being of pets and livestock by continuously detecting physiological and behavioral data [8]. Smart wearables utilize Global Positioning System (GPS) and Artificial Intelligence (AI) to monitor animal health, providing real-time feedback and remote monitoring, enabling early diagnosis, individualized care, and effective communication between veterinarians, pet owners, and animals [9]. Animal anxiety management poses challenges such as not being able to correctly identify indicators of anxiety in animals, no standardized practice guidelines, limited access to technology, high implementation costs, and weak regulation enforcement, which can prevent consistency in delivery care and also affect the success of putting a smart solution in place to regulate anxiety [10].

The intent of the investigation is to evaluate a smart wearable that can monitor and manage anxiety in pet dogs using deep learning (DL) algorithms and piezoelectric thin-film materials. The research utilizes the Tangent Search-driven Stacked Convolutional Neural Network (TS-StackedCNN) model to analyze and detect anxiety regulation in pet dogs.

The following sections comprise the research: Section 2 outlines relevant literature, Section 3 explains methodology, Section 4 gives findings and discussion, and Section 5 concludes the research.

2. Related Work

Research compared two patient groups: one walking with a dog and a handler, and another taking a walk without a dog [11]. Results showed that the dog group reported significantly less anxiety, fear, and heart rate levels compared to the other group. Limitation factors included a small sample and a need for expanded research to establish the generalization of findings. The role of pet attachment and, more specifically, attachment to a dog in decreasing anxiety and depression, in particular with women who have a history of childhood abuse, was examined [12]. Limitations of the research include cross-sectional designs and self-report measures of previous history, highlighting the need for longitudinal studies to make firmer conclusions. The importance of gut microbiota for canine anxiety disorders, noting the effect of dysbiosis on mental health through multiple biological pathways, was described [13].

However, the research was plagued by limitations, with a notable lack of research specifically aimed at dogs. To examine the efficacy of DìRelaxTM, a nutraceutical designed for reducing dog anxiety, Root Canal Therapy (RCT)-type research was examined [14]. Results indicated improved cognitive performance on solvable tasks and some behavior improvements, and no adverse effects were documented. Limitations included the need for more research on the optimal way to administer the intervention and improvement during the unsolvable phases was not observed. The impact of companion dogs and cats on young adults' mental health was discussed, along with topics on the effects of stress, anxiety, and depression [15]. The findings illustrate that pets were a positive factor in controlling the symptoms of mental illness and overall wellbeing. The limitations of the research included a small sample and possible biases from self-reporting. The research proposed using trauma-informed care (TIC) in canine behavioral evaluations, especially in fearful-aggressive dogs that could have had previous trauma [16]. The research found that a deeper understanding of a dog's negative associations through the lens of empathy could enhance treatment. Limitations were the difficulties with obtaining the specific trauma histories, and the limited evidence-based research on TIC with dogs. A research model to better understand pet food anxiety, specifically during the COVID period, while examining factors like pet owner perceptions, interactions, and prior food insecurity, was examined by [17]. TIC found that an emotional bond with their pet and past experiences with food scarcity contributed to inflated anxiety, which subsequently affected their behaviors towards feeding and shopping.

3. Materials and Methods

The procedure for gathering data is described in the section. Following compilation, the data is subjected to preprocessing using the Gabor filter. The LDA is exercised to extract features from detecting anxiety regulation. A TS-StackedCNN model is applied to analyze and detect anxiety regulation in pet dogs. Figure 1 provides a visual presentation of the proposed workflow.

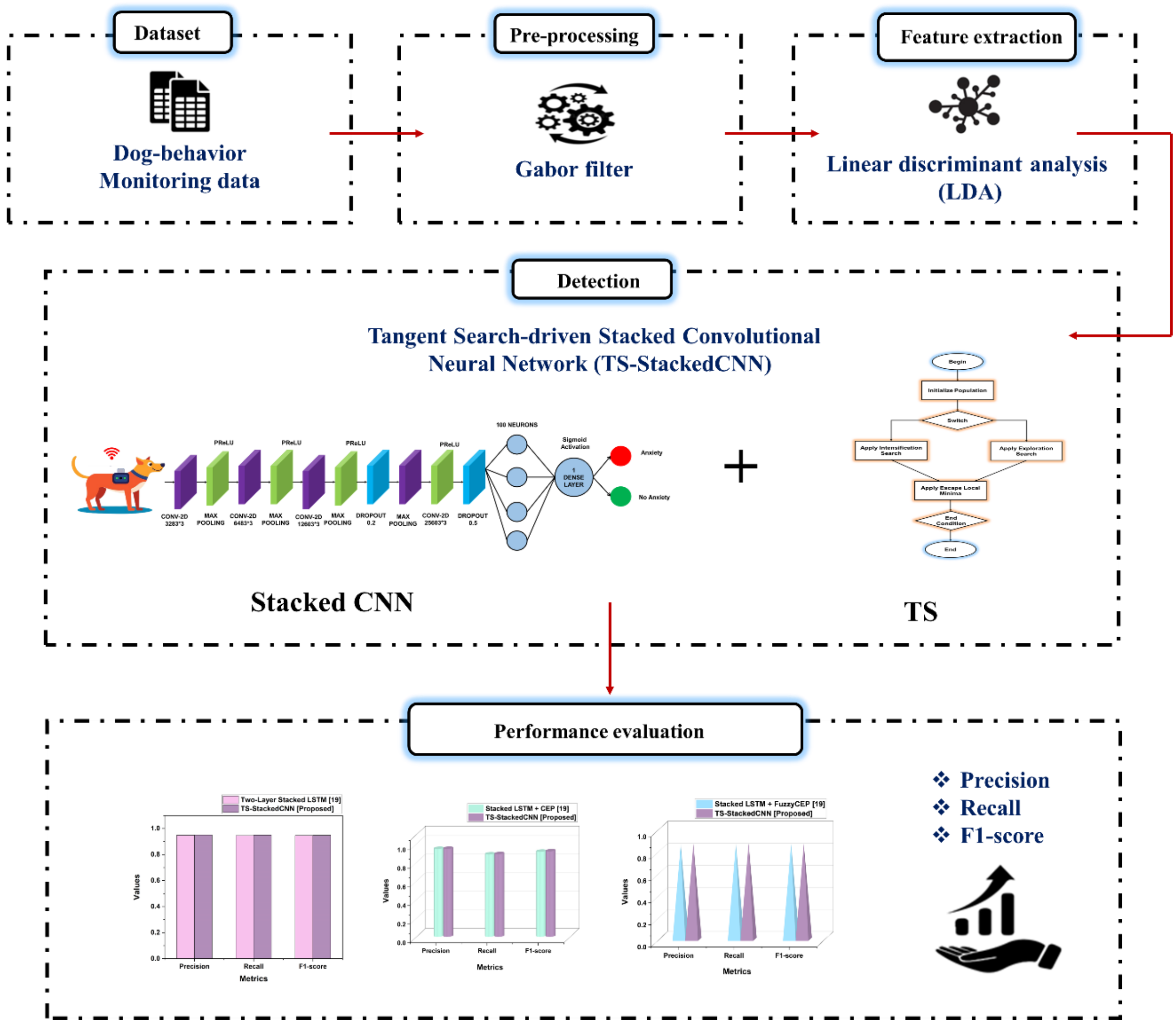

Figure 1.
Overall proposed flow.

Edelweiss Applied Science and Technology
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3.1. Data Collection

In this research, data utilized in the Kaggle dataset [18] depicts the potential behavior of a dog over a 60-second duration at a 50 Hz sample rate (50 samples per second) with a simulated sensor reading, as well as inferred behaviors based on head and body position. This dataset does include several behaviors that can be studied or analyzed for attributes of dog behavior, which can help in several things, such as animal behavior analysis, training systems or health monitoring.

3.2. Pre-Processing Using Gabor Filter (GF)

The purpose of the GF in the research is to preprocess the raw sensor data taken from the dog behavior monitoring dataset before use in the DL model. The GF enhances sensor data clarity, reduces background noise, and identifies anxiety-related behavior by capturing specific spatial frequencies and orientations, enhancing micro-vibrational movements during stress. $w \, and \, Z$ are the original coordinates, while $w' \, and \, z'$ are the transformed coordinate after rotation by angle θ. $\gamma \, and \, \sigma$ control the shape and width of the gaussian envelope. $e \, and \, \omega$ define the frequency and angular frequency of the sinusoidal oscillation. η normalizes the function, and j is the dogs behavior unit for the oscillatory component, as described in equations (1-2).

$$Gabor(w,z) = \frac{e^2}{\pi\gamma\eta} exp\left(-\frac{w'^2+\gamma^2 z'^2}{2\sigma^2}\right) \times \exp\left(j.(2\pi e w' + \omega)\right) \quad (1)$$

$$w' = w\cos\theta + z\sin\theta \quad (2)$$

3.3. Linear Discriminant Analysis (LDA) for Feature Extraction

Through feature extraction, new dimensions are created by mixing with previous dimensions. The efficacy is assessed using the outcomes of randomized testing. One method of discriminating based on class is LDA. State-of-the-art feature extraction approaches, such as LDA, were combined to improve the accuracy of anxiety detection in pet dogs with stackedCNN algorithms to provide an intelligent, non-invasive method to measure and control anxiety levels in real-time. This technique aids in the discovery of a set of basis vectors using supervised learning. These basic vectors are represented by the letter w_k. The $w_k$vectors are the maximum percentage of the original instance sets inside and between-class dispersals. The generalized eigenvalue problem for finding w_k basis vectors is solved.

$$X_{opt} = \underset{\omega}{argmax} \frac{|X^S T_D \, X|}{|X^S T_v \, X|} = [\omega_1, \omega_2, .., \omega_K] \quad (3)$$

Where, $K = dubspace'sdimension, T_D = between \, and \, T_v = withinclasses.$

$$T_D = \sum_{l=1}^{b} N_l \, (\mu_l - \mu)(\mu_l - \mu)^S \quad (4)$$

$$T_U = \sum_{l=1}^{b} \sum_{wv \in W_l} (w_v - \mu_l)(w_v - \mu_l)^S \quad (5)$$

Where,$b = no. of \; class, W \in Q^M = sample, W_l = sample, N_l = no. of \; classink,$ and$\mu = mean$. The base vectors wk that are needed in Equations (2), (3), and (4) are the first L largest eigenvalues$\{\Psi_l \mid 1 \leq l \leq K\}$, provided that SV is not singular. Since the initial vectors of LDA were perpendicular to their neighbors, it is estimated into the LDA subspace to obtain its representations by applying a simple linear techniqueWTx. The anxiety detection system with feature extraction and LDA was improved to obtain better-performing models in the setting of wearable sensors.

3.4. Detection Using Tangent Search-driven Stacked Convolutional Neural Network (TS-StackedCNN)

A TS-StackedCNN is designed to carry out deep feature learning while benefiting from metaheuristic optimization. Through the use of the TSA to fine tune hyperparameters and stackedCNN to layer features hierarchically, the hybrid method is capable of detecting canine anxiety accurately and reliably based on physiological signal patterns identified from wearable sensors.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
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3.4.1. Stacked Convolutional Neural Network (StackedCNN)

The suggested StackedCNN model's structure, which is displayed in Figure 2, has been constructed to accommodate real-time dog behavior-conducive processing of physiological signals for identifying the minutiae of anxiety. The model was trained with a focus on progressive feature extraction, which was integral to the interpretation of sensor-derived dog behavior with real-time changes detailed in muscle tension or posture. The CNN is well suited to handle the type of dog behavior since filters can detect local and abstracted forms of stress detections and behaviors that are atypical.

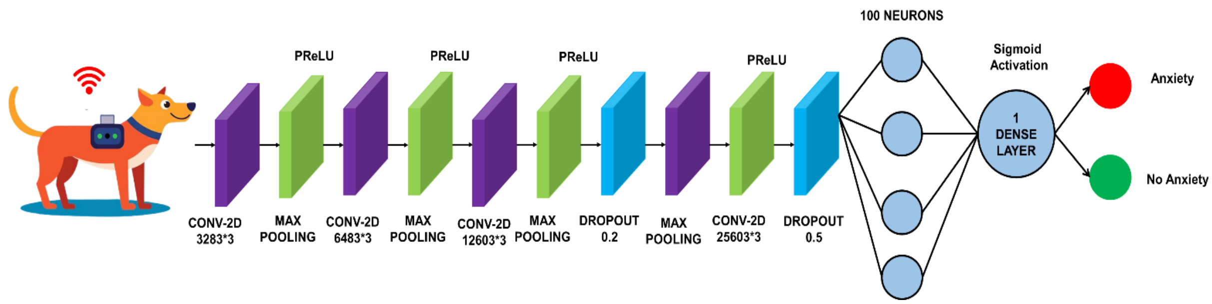

Figure 2.
Architecture of StackedCNN.

The model consisted of four Conv2D layers with 32, 64, 128, and 256 corresponding filters, respectively, and each layer was followed by Max Pooling to purposefully reduce dimensions while minimizing overfitting, yet allowing the retention of spatial hierarchies for representing sensor signals. The final feature maps were then flattened into a single row and passed to a dense layer containing 100 neurons using a sigmoid activation function to develop complex non-linearities for either binary or multi-class pet dog anxiety classifications. All training used a 90:10 data split, implementing TS optimization to provide a heightened convolutional weight and parameter adjustment strategy, which avoided local minima, shifting system outputs towards increased predictive reliability. In StackedCNN, Parametric ReLU (PReLU) was used instead of ReLU. PReLU when deciding the activation function for the hidden layers, consider the PReLU as the activation function rather than the standard ReLU. PReLU takes care of dead neurons (neurons that never activate during training) and can improve training dynamics to obtain better model performance.

3.4.2. Tangent Search (TS) Algorithm

The TS is an optimization algorithm that balances increase and exploration to avoid convergent and divergent solutions. The TS is used to refine the parameters of the underlying StackedCNN model to improve the accuracy of anxiety detection in dogs, as shown in Figure 3. To increase the pace of convergence and the quality of the solutions, TS provides a hybrid technique by combining three essential elements: local minima escape, intensification, and exploration. The combination optimizes the search process and improves the ability to find high-quality solutions, making it a powerful tool for complex optimization problems.

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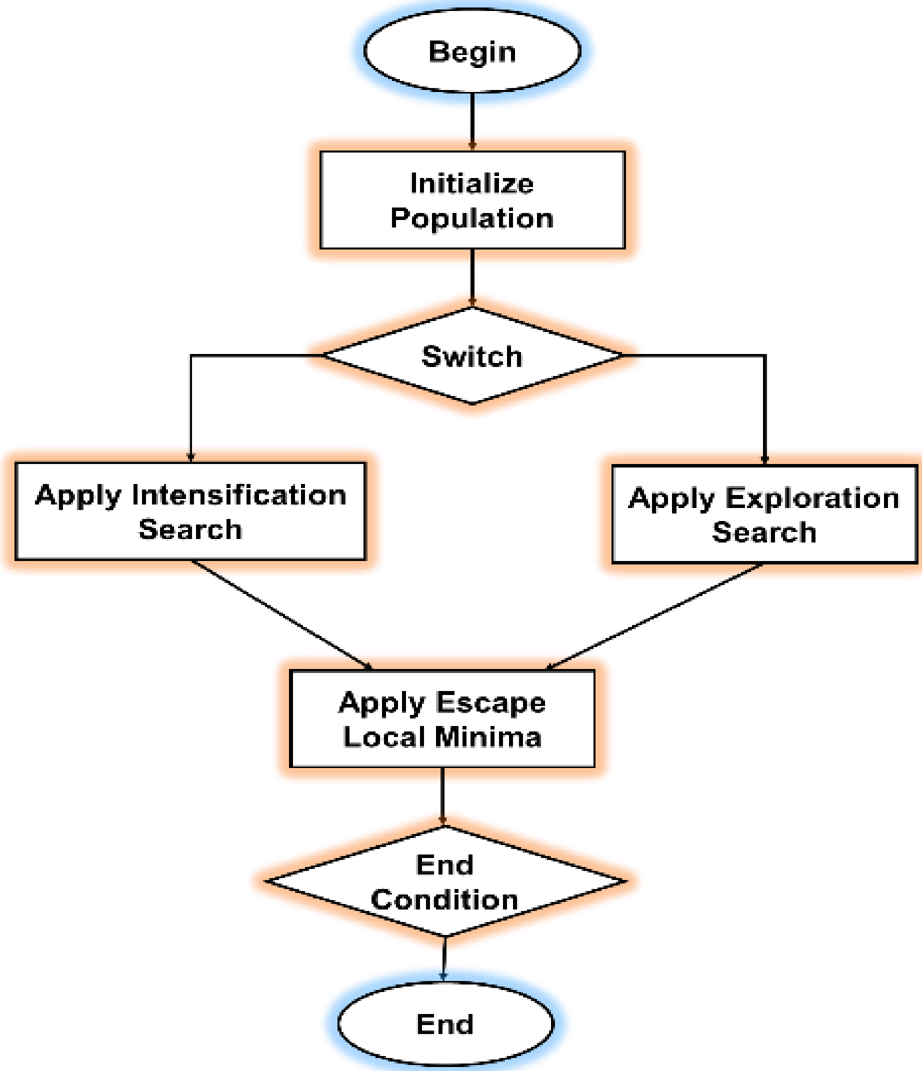

Figure 3.
Flow diagram of TS.

Initial Population Development: The TS process generates an initial population within the search space and rand, a function that produces random integers between 0 and 1 that are evenly distributed, with the problem dimension. Initial solution is uniformly distributed over the entire search space and serves as the starting point for the algorithm. TS first initializes a diverse population of possible network parameter configurations, as described in Equation (6).

$$W = lb + rand(0,1) \times (ub - lb) \tag{6}$$

W is the solution vector, $lb \; and \; ub$ are lower and upper bounds, $rand \; (0,1)$ produces uniformly distributed random values.

Search intensification: In the intensification search, TS first makes a random local walk, which is directed by Equation (7). Then, TS replaces some of the variables in the solution obtained in the random local walk with the corresponding variable values from the current optimal solution. For problems with a higher dimension, the proportion is set at 20%, and 50% is used when problems have less than or equal to 4 variables. TS also has been a localized search method as a way to speed up the convergence of the

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DL model to good-performing parameter sets. The localized search is a way to get the candidate solutions closer to the best-observed configuration, which is critical to the ability to accurately detect patterns of anxiety from continuously observed real-time physiological signals.

$$W_j^{s+1} = W_j^s + step \times \tan(\theta) \times (W_j^s - W_j^{opt}) \quad (7)$$

Selected variables can be replaced directly with values from the current optimal solution. $W_j^{s+1} = W_j^{opt}$ if variable j is selected. To ensure boundary compliance, any out-of-range value is repaired as $W = lb + rand\,(0,1) \times (ub - lb) \quad if\ w < lb\ or\ W > ub$. The phase improves model performance locally by utilizing known good solutions.

Exploration search: TS uses a new global random walk based on the tangent flight principles. The tangent function allows the random walk to better search the space. The angle θ being near $pi/2$ will allow the tangent to be a larger value and the solution will be far from the current solution, as on the contrary, the angle θ being near 0 will provide smaller values to the tangent and the new solution should be very close to the current solution. Thus, the exploration search in Equation (8) includes the global and local random walk for exploration.

$$W_j^{s+1} = W_j^s + step \times \tan(\theta) \quad (8)$$

The angle θ determined the step size small near (0) and large near $\frac{\pi}{2}$, thus providing a flexible mechanism to explore the solution space efficiently.

Escape local minimum procedure: To address the problem of becoming stagnant in local minima during the optimization process. TS has a means of dealing with the problem as it uses some specific process as shown in equations (9) and (10). The process can be broken down into two components, which are carried out with some probability O_{sec}. In addition, sometimes with a 0.01 probability, a random solution takes the place of the worst solution. TS employs a stochastic local escape strategy as part of the wearable system's deep model training.

$$W = W + rand(0,1) \times (W^{opt} - W) \quad (9)$$

$$W = W + rand(\theta) \times (ub - lb) \quad (10)$$

An enhanced TS variant in which the algorithm consists of just two parts: intensification and exploration components without an escape local method. The TS-StackedCNN will enhance its predictive accuracy through TS optimization of the final layer's weights. The post-classification hybrid contribution will improve generalization, misclassification, and the eventual robustness in recognizing minor physiological variations, and will provide greater accuracy and reliability in detecting anxiety in dogs. TS-StackedCNN is described in Algorithm 1.

Algorithm 1: TS-StackedCNN
Step 1: Dog behaviour Preprocessing
For each raw sensor signal:
    Normalize the sensor data
Step 2: Define CNN Architecture
Conv2D Layer 1 (filters=32) → MaxPooling
Conv2D Layer 2 (filters=64) → MaxPooling
Conv2D Layer 3 (filters=128) → MaxPooling
Conv2D Layer 4 (filters=256) → MaxPooling
Flatten → Dense(100) → Sigmoid Activation
Step 3: Tangent Search Algorithm Initialization
Define population size N and dimensions D
For each individual i in the population:

$$W\_i = lb + rand(0,1) * (ub - lb)$$

Step 4: Model Training with TS
Repeat for S iterations:

For each solution W_i:

$$accuracy\_i = TrainAndEvaluateCNN(W\_i)$$
$$W\_best = solution\ with\ the\ highest\ accuracy$$

Intensification (local search)

For each W_i:

If rand < intensify_prob:

θ = random_angle()

$$W\_i = W\_i + step * tan(\theta) * (W\_i - W\_best)$$

Replace out-of-bound values

Exploration (global search)

For each W_i:

If rand < explore_prob:

$$\theta = random\_angle()$$
$$W\_i = W\_i + step * tan(\theta)$$

Replace out-of-bound values

Escape from local minima (occasional random jump)

If rand < 0.01:

Replace worst W_i with a random solution

Step 5: Final Training with Optimized Parameters

Train final CNN using W_best

Evaluate on test set

Return

4. Results and Discussion

This section deliberates on the results produced by the implementation of the model, including parameter setup, evaluation criteria, and comparative phase. Every experiment was carried out in a Windows 10 environment with 16 GB of RAM and a 64-bit Intel(R) Core (TM) i7-7500U CPU. The models were implemented using Python v3.8.2 and the PyTorch v1.9.0 package.

4.1. Performance Evaluation

Figure 4 (a) is a bar plot that displays the frequency distribution of atomic behaviors (Standing, Lying, Digging, etc.), with frequencies on the y-axis. Standing is the most frequent behavior, while Sniffing and Barking occurred less often. Figure 4 (b) is a heatmap showing the correlation between different body parts (the neck and back) along the x, y, and z axes. The correlation values are generally low, indicating there are little to no relationships between the movement of the neck segment and the movement of the back segment across different axes.

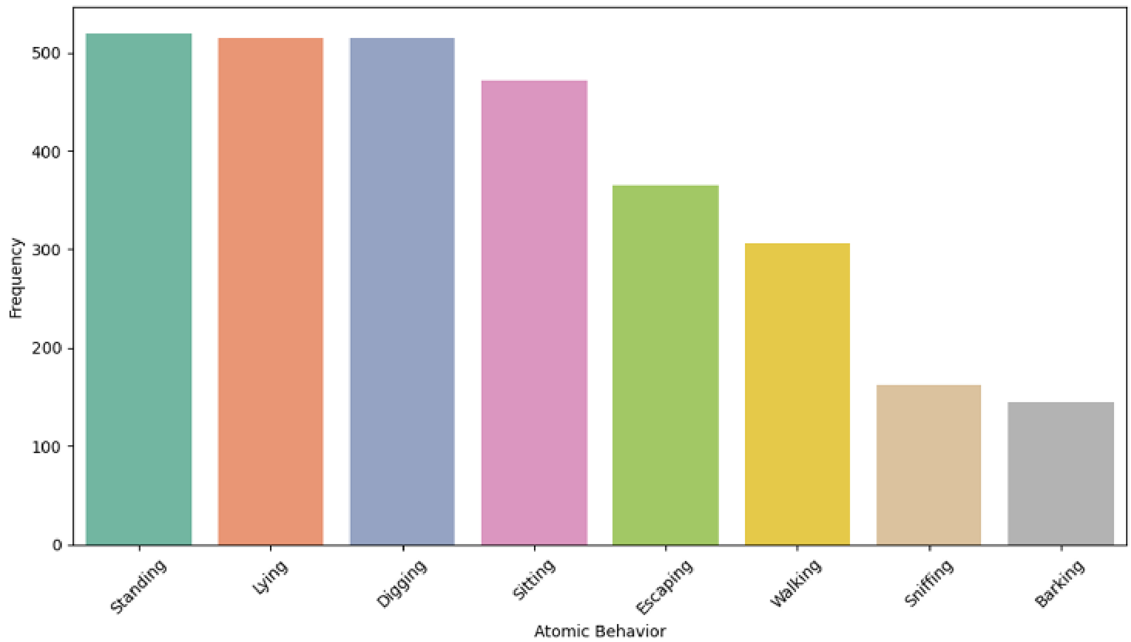

Figure 4.
(a): Atomic behavior frequencies sensor data.

Figure 4.
(b): Correlation of heatmap of neck and back sensor data.

4.2. Comparison Evaluation

The proposed method, TS-StackedCNN, compared to Two-Layer Stacked LSTM, Stacked Long Short-Term Memory (LSTM) with Complex Event Processing (CEP) and fuzzy logic (Fuzzy-CEP)

[19] methods for monitoring pet dogs psychological Separation Anxiety (SA) symptoms; the comparison was evaluated in terms of precision, recall, and F1-score to measure each activity based on levels (Level 1, 2, and 3) recognition performance.

Precision: Precision demonstrates the number of true anxiety detections compared to all predicted anxiety detections. Meaning it displays how well the model works to limit false positives, and thus flagged only anxious dogs. The system was good at the task because of the learning and classification of features.

Recall: Recall evaluates the capability of identifying every actual anxiety occurrence. It is primarily concerned with how accurately the system can identify true anxiety from the sensor data and, by capturing more true cases, reduce the chances of missing a real case. A high rate of recall means the model is trustworthy enough to inform a behavioral intervention through physiological monitoring.

F1-score: The F1-score balances false positives and false negatives by taking the harmonic mean of accuracy and recall. It represents the model performance in discerning canine anxiety with accuracy and consistency. It is crucial for the hybrid system to have dependable stability in real-time emotional state recognition.

According to Table 1 and Figure 5, the Two Layer Stacked LSTM performed well, achieving an F1-score of 0.947, an precision of 0.948, and a recall of 0.946. With an precision of 0.950, recall of 0.949, and an F1-score of 0.948, the suggested TS-StackedCNN performs marginally better, indicating that it is marginally more effective in identifying anxiety in dogs.

Table 1.
Performance of Level-1 postures.

Methods	Metrics		
	Precision	**Recall**	**F1-score**
Two-Layer Stacked LSTM [19]	0.948	0.946	0.947
TS-StackedCNN [Proposed]	0.950	0.949	0.948

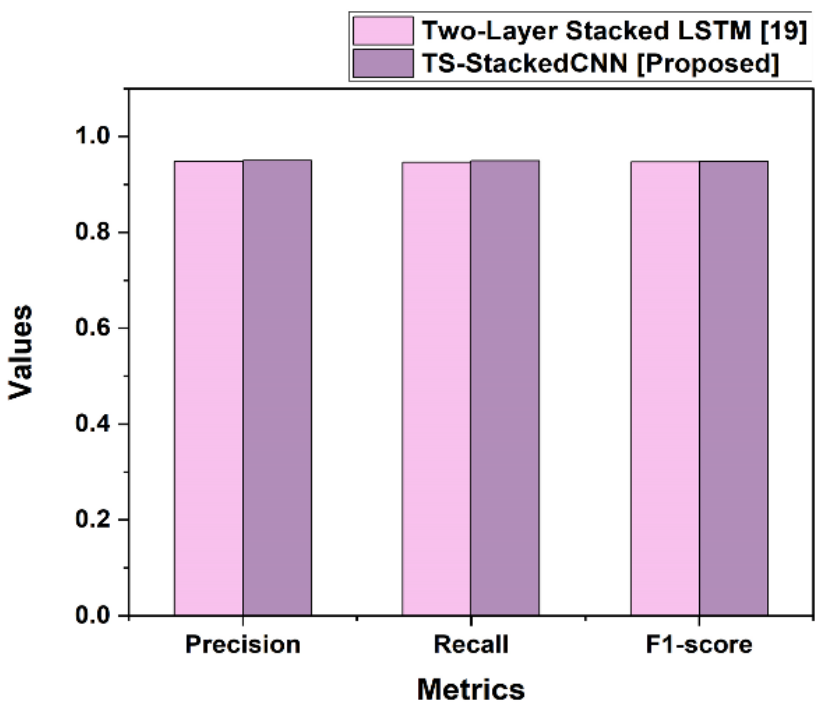

Figure 5.
Comparison of Level-1 postures.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4: 2976-2989, 2025
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Table 2 and Figure 6 demonstrate that the Stacked LSTM + CEP method achieves a precision of 0.945, a recall of 0.886, and an F1 score of 0.915, while the TS-StackedCNN model achieves a slightly better precision of 0.946, a recall of 0.889, and an F1 score of 0.919. This indicated that the TS-StackedCNN model presented a more balanced and somewhat more successful strategy for identifying anxiety in companion dogs, given the minor gains in overall precision, recall, and F1 score.

Table 2.
Precision, recall and f1-score Performance of Level-2 postures.

Methods	Metrics		
	Precision	Recall	F1-score
Stacked LSTM + CEP [19]	0.945	0.886	0.915
TS-StackedCNN [Proposed]	0.946	0.889	0.919

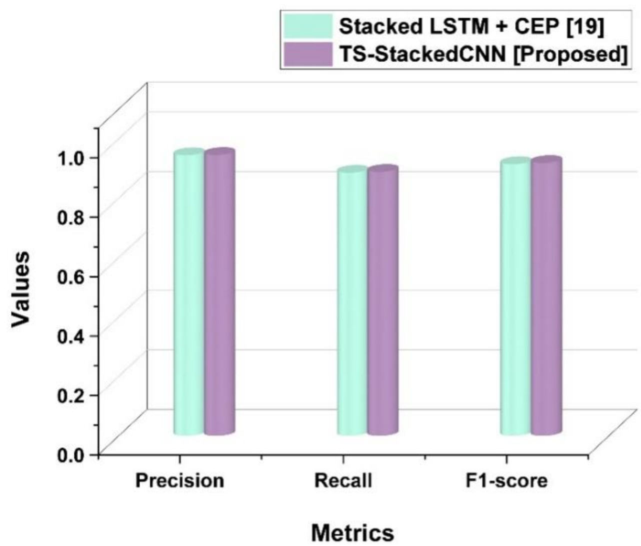

Figure 6.
Precision, recall and f1-score comparison of Level-2 postures.

Table 3 and Figure 7 display the performance of the Stacked LSTM + Fuzzy-CEP model, which achieves a precision of 0.862, recall of 0.864, and F1-score of 0.863. The proposed TS-StackedCNN model has a very slight improvement, with a precision of 0.864, recall of 0.868, and F1-score of 0.865. Therefore, it is suggested that the proposed TS-StackedCNN model performed a little bit better in terms of precision and recall, validating its performance in detecting anxiety in pet dogs.

Table 3.
Outcomes of Level-3 postures.

Methods	Metrics		
	Precision	Recall	F1-score
Stacked LSTM + Fuzzy-CEP [19]	0.862	0.864	0.863
TS-StackedCNN [Proposed]	0.864	0.868	0.865

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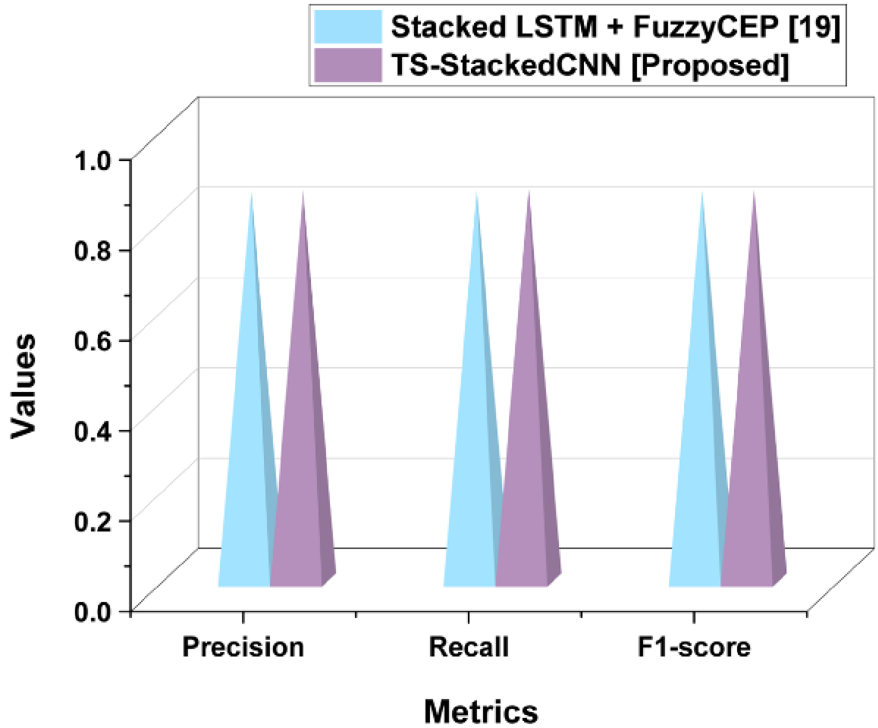

Figure 7.
Representation of Level-3 postures.

DL algorithms are used in smart wearable pet solutions to control and manage anxiety in dogs. The Two-Layer Stacked LSTM is proficient in capturing temporal dependencies but limited in its ability to extract spatial features, which negatively impacts the overall precision and adaptability to variations in input complexity. Stacked LSTM + CEP do improve the context in the data set, but it has been noted that the lower recall can arise due to a lack of likelihood of spatial representation. Similarly, Stacked LSTM + Fuzzy-CEP incorporated fuzzy logic to help acknowledge uncertainty, while this led to the previous method lacking in depth of feature learning and consequently performing moderately. Thus, the introduced method, TS-StackedCNN, provides and demonstrates how temporal and spatial learning can be integrated, using hybrid architecture to enable continuity in sequential dependence while providing localized features. Furthermore, the ability to generalize and learn from both the temporal and spatial domains likely contributes to the overall improvement in all key metrics, as well as providing more accurate and robust prediction on dynamic strength, developed via additive manufactured composite materials.

5. Conclusion

A novel method utilizing a TS-StackedCNN model integrated with smart thin film sensors to detect, and mediate canine anxiety. The data confirms that anxiety was categorized into three levels of severity - Level 1 indicates no anxiety, Level 2 indicates moderate anxiety, and Level 3 indicates high anxiety. The first step in preparing the raw sensor data for analysis was applying a Gabor filter during preprocessing to remove noise and outliers so that features that would be related to the data could be further analyzed. Features are then extracted by Linear Discriminant Analysis (LDA), that is, identifying the features that separate the different levels of anxiety. With level 1 (accuracy of 0.950, recall of 0.949, and F1-score of 0.948), level 2 (precision of 0.946, recall of 0.889, and F1-score of 0.919), and level 3 (precision of 0.864, recall of 0.868, and F1-score of 0.865), the TS-StackedCNN model showed high performance following feature extraction. One limitation within this research is the use of only a single dataset, which does not represent the full range of dog behaviors in multiple settings. Future research should investigate expanding the dataset across various breeds and settings, which would allow for improved generalization of the model, as well as adding additional sensors to detect and regulate anxiety more fully.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4: 2976-2989, 2025
DOI: 10.55214/25768484.v9i4.6703