



ENHANCING LOCOMOTION MODE RECOGNITION ACCURACY: A DEEP LEARNING MODEL FOR NOISY LABEL HANDLING

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ABSTRACT

The availability of various sensors in smartphones has made it easier to collect human locomotion data. This data is useful for recognizing different locomotion modes namely walking, cycling and traveling. The correct identification of locomotion modes helps in transportation planning, traffic analysis and travel cost estimation. In most cases, these labels are assigned through crowdsourcing or web-based queries. This paper presents a deep learning-based approach for locomotion mode recognition in the presence of noisy labels. The proposed method builds an ensemble model consisting of three sub-models. The different models were created for processing training data with varying degrees of noise contaminations. A conventional deep learning system obtains spatial-temporal information from basic sensor inputs. The model maintains reliable performance within conditions of minimal label noise. A noise adaptive model contains a dynamic loss function which adjusts its operation according to noise intensity levels. The model shows success in dealing with intense noise levels. The proposed approach showed its effectiveness through experiments conducted on both newly obtained datasets and pre-existing available datasets. This paper resolves the problems with noisy labels which occur in locomotion mode recognition tasks. The ensemble model achieves recognition success through its integration of conventional, adaptive and corrective techniques.



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I. INTRODUCTION

Research into identifying human movement patterns constitutes the main subject of locomotion mode recognition [1]. The technique supports technology applications dedicated to transportation planning and health monitoring and traffic analysis systems. Smartphones and wearable devices have become important tools for collecting movement data because of improving sensor technology. Real-time motion characteristics are tracked through the sensors which include accelerometers and gyroscopes and magnetometers on these devices [2]. Multiple applications benefit from determining walking, running and cycling and motorized transport activities. The technology enables professionals to evaluate the time needed for travel alongside transport expenses while calculating traffic conditions [3]. Correct identification of locomotion modes through analysis leads to superior transportation solutions and helps in better urban development. High accuracy in locomotion recognition depends on how well the training data quality supports machine learning models.

The development of deep learning tools offers a reputable method for handling raw sensor data and extracting fundamental characteristics from it [4]. Time-series pattern recognition often relies on the combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks as per studies in reference [5]. Such models extract important features from original signal data before achieving strong performance in locomotion activity identification. The implementation of deep learning models depends heavily on enormous datasets that need thorough human labeling. Data labeling usually takes place through crowdsourcing platforms and web-based queries until all training materials get properly annotated [6]. Users and volunteers apply labels to sensor data examples that later help develop machine learning model training programs. This annotation method contains multiple potential errors that occur during its execution. The poor data labeling by non-specialist volunteers happens when they misinterpret information and lack sufficient knowledge [7]. Because of improper labeling the datasets end up containing inaccurate information that creates difficulties for recognition model performance. The presence of noisy labels creates inconsistencies which affect the training procedure [8]. Deep learning models learning from erroneous labels will create prediction errors. Accurate classification stands as a crucial requirement for locomotion mode recognition since exact identification is vital for executing decision-making operations. Noisy labels represent a main issue which demands immediate attention by researchers in the field. The proposed research introduces a brand new deep learning method to detect locomotion patterns when dealing with noisy label data.

The proposed procedure implements an ensemble model which unifies three different deep learning systems. The designed models allow processing data with various levels of training dataset noise [9]. The ensemble model operates through automatic selection of the most appropriate model when it detects specific levels of noisy labels. The ensemble model implements weighted averaging to combine these three models according to the paper [10]. Each model receives its weights dynamically based on the detection of noise in the dataset. The technique described in this paper provides methods to determine noisy label concentration within a dataset. The ensemble model distributes fractional weight values to each of its sub-models. Dataset label noise levels can be measured using the weight values present in these models [11]. The proposed model allows the conventional model to control the classification process when noise concentrations remain low. The noise corrective model adopts priority over the conventional model as the noise concentration level increases above specific values. The proposed method shows its effectiveness based on experiments done with existing and gathered datasets as reported in [12]. The dataset obtained through smartphone sensor data collection operates alongside other established datasets that contain publicly accessible data regarding locomotion mode recognition. Testing confirms that the proposed approach surpasses standard deep learning approaches which fail to handle noisy labels. The ensemble model demonstrates superior accuracy performance while offering superior resistance to noise than conventional methods according to [13]. The key contributions of this paper are:

- The research implements a recent deep learning protocol dedicated to identify locomotion types from uncertain sensor measurements.
- The project aims to create a hybrid model which combines regular techniques with noise-adjusting and noise-correcting models. A loss function is introduced which adjusts itself according to the diverse noise levels within training data.
- A low-rank approximation method works to recover original labels from data with noise. The system requires experimental testing on gathered datasets and available information for assessing its operational effectiveness.

Intelligent transportation systems together with mobility analysis require recognition of locomotion modes as their essential element. The research solves the recognition accuracy problem in noisy environments through the design of an ensemble deep learning framework. The proposed method implements a reliable system to handle imperfect labelling data found in real-world applications. The proposed method will be expanded to encompass recognition of activities in healthcare applications along with smart city programs in forthcoming research studies.

II. RELATED WORK

Researchers extensively study recognition systems for various movement patterns during the past years. The enhancement of classification accuracy through sensory data has been examined through different techniques by research teams. The traditional method used machine learning algorithms consisting of SVM alongside Decision Trees and k-Nearest Neighbors (k-NN) [14], [15]. The methods needed human operators to create features which hampered their performance when analyzing complex locomotion data. The growth of deep learning enabled researchers to start applying CNNs to recognize human locomotion patterns. The spatial features within sensor data can directly be learned by CNNs which results in enhanced classification ability [16], [17]. The temporal relationships in time-series sensor information can be tracked through the use of LSTM networks [18]. These models outperform traditional methods in accuracy and generalization. The main difficulty in locomotion mode recognition occurs because training data contains numerous noisy labels. Noisy labels result from errors in crowdsourcing, incorrect user inputs or sensor malfunctions. To address this issue, researchers have developed noise-robust learning techniques. One such approach involves modifying loss functions to make models less sensitive to label noise [19]. Another method focuses on data filtering, with samples of high label uncertainty are removed [20]. Several studies have proposed ensemble learning methods to improve robustness against noisy labels.

These approaches combine multiple classifiers to achieve better generalization [21], [22]. The ensemble model introduced in this paper follows a similar strategy by integrating conventional, noise adaptive and noise corrective models. Deep learning models are known to memorize noisy labels, which affects the performance over time. Researchers have explored semi-supervised learning methods to mitigate this issue. Semi-supervised techniques utilize both labeled and unlabeled data to improve model robustness [23]. This strategy helps prevent overfitting to incorrect labels and enhances generalization. Another approach to handling noisy labels is using low-rank approximation techniques. This method assumes that correctly labeled data follows a low-rank structure, while noisy labels introduce inconsistencies [24]. By estimating a low-rank approximation of the label matrix, models correct mislabeled instances, thereby improving classification accuracy. The noise corrective model proposed in this paper is based on a similar concept. Existing literature also explores active learning strategies, with uncertain samples queried for relabelling [25]. This method proves that models learn from high-quality labeled data, reducing the impact of noise. However, active learning requires human intervention, making it less scalable for large datasets. Furthermore, researchers have investigated data augmentation techniques to improve model robustness against label noise [26].

Synthetic data generation and transformations help models generalize better by exposing them to varied representations of locomotion patterns. However, most existing techniques require prior knowledge of noise concentration. The approach proposed in this paper overcomes this limitation by dynamically selecting the best model based on noise levels.

III. PRELIMINARIES

Locomotion mode recognition relies on sensory data collected from devices like smartphones and wearable sensors. These devices provide raw data that must be processed using mathematical models and deep learning techniques. This section presents the essential concepts and notations used in this study. Let $D = \{X_{tr}, Y\}$ be the labeled training dataset, here $X_{tr} \in \mathbb{R}^{N \times M}$ represents N labeled instances, each consisting of M data points. The label matrix $Y \in \mathbb{R}^{N \times k}$ is a one-hot encoded representation of k class labels. Each element in Y takes a value of either 0 or 1. The element $Y(i, j) = 1$ if the i -th instance belongs to the j -th class. In practice, the training dataset often contains noise in labels. We define a noisy label matrix Y' , with some labels incorrectly assigned. The objective of locomotion mode recognition is to learn a mapping function $H: X_{tr} \rightarrow Y$, such that the classifier correctly predicts the labels despite the presence of noisy data. Noisy labels introduce incorrect mappings between input data and class labels. We define the probability of a true label t_i for instance i as:

$$t_i = 1, \text{ if } Y_i = Y'_i; \\ \frac{k-2}{k-1}, \text{ otherwise} \quad (1)$$

This formulation helps in estimating the probability that a given label is correct. When the variance of loss across instances is low, the dataset is assumed to have minimal noise. If the variance is high, noise is present and corrections are needed. A common strategy for handling noisy labels is estimating a low-rank representation of the label matrix. Let T be a low-rank matrix that approximates the true label distribution. The objective is to minimize:

$$\min_T \text{rank}(T) \quad \text{subject to } T(i, j) = Y'(i, j) \quad (2)$$

This problem is solved using trace norm minimization. A low-rank representation effectively filters out label noise, achieving that training labels align closely with the actual distribution. Deep learning models minimize a loss function to optimize classification performance. For noisy labels, we introduce a modified loss function:

$$L_{NAL} = -\frac{1}{N \times k} \sum_{i=1}^N \sum_{j=1}^k \left[ab(t_i \log r_{ij}) + (1-a)r_{ij} \log t_i + (1-b)(1-t_i) \log(1-r_{ij}) \right] \quad (3)$$

Here, a and b are dynamic parameters adjusted during training. The loss function penalizes false predictions and reduces the impact of label noise on model learning. To improve classification performance, this work adopts an ensemble learning strategy. The Conventional Model extracts both spatial and temporal features from raw sensor data. It processes data using deep learning techniques like CNN and LSTM. This model helps identify movement patterns but struggles with noisy labels. It serves as the base for further improvements. The Noise Adaptive Model introduces a dynamic loss function. It adjusts predictions by detecting and adapting to noise levels in the dataset. The Noise Corrective Model applies a low-rank approximation technique. It improves noisy labels by estimating true labels from corrupted data. These three models work together in an ensemble to improve accuracy and robustness. The final classification decision is obtained using weighted aggregation of the model outputs:

$$Y_{te} = \sum_{i=1}^3 \alpha_i Y_{te}^i, \quad \text{where } \sum_{i=1}^3 \alpha_i = 1 \quad (4)$$

Adjustable weights α_i adapt themselves to the amount of noise in order to maximize model validity for final predictions. A comprehensive introduction of vital mathematical symbols linked to noise management techniques for locomotion mode identification systems occurred within this segment. The proposed approach gets detailed explanation in the following section about model architecture and implementation strategies.

IV. LOCOMOTION MODE RECOGNITION APPROACH WITH NOISY LABELS

Human activity analysis heavily relies on detecting and recognizing different movement patterns. Through this technique analysts can detect three fundamental transportation methods from sensor information. A deep learning approach with noise labeling management capabilities will be explained for improving classification accuracy. The Figure 1 shows a decision system which addresses noisy labels during machine learning classification tasks. The system contains multiple elements that start with Dataset D functioning as an input data source. The system directs Dataset D through three models including Conventional Model, Noise Adaptive Model and Noise Corrective Model. Traditional features and spatial patterns from raw sensors drive the Conventional Model to produce traditional outputs. The Noise Adaptive Model adjusts predictions by introducing a dynamic loss function that accounts for noise levels in the data. The Noise Corrective Model applies a low-rank approximation technique to estimate the true labels and correct misclassifications. These three models work together to improve classification performance. The outputs from all three models are fed into the Ensemble Model, with an Optimization process determining the best weight distribution among the models. This ensemble approach results the system to prioritizes the most reliable model based on noise levels.

The optimized classification is then sent to Classifier II, which processes the Testing Instance to generate the Testing Labels. This final classifier improves the predictions and results robustness in the presence of label noise. The entire framework improves the classification process by reducing errors caused by noisy labels and enhancing model generalization. The combination of multiple models with adaptive noise handling makes this approach more effective in real-world applications with data uncertainty as common.

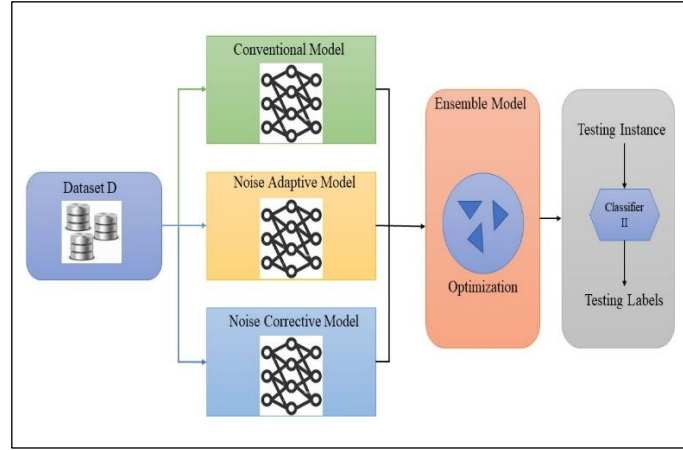


Figure 1: Block diagram of LRNL approach with its components.

Source: Authors, (2026).

The Conventional Model extracts spatial and temporal features from raw sensor data. It processes information using deep learning techniques like CNN and LSTM. This model helps in recognizing locomotion modes but struggles with noisy labels. It serves as the foundation for further improvements. The Noise Adaptive Model introduces a dynamic loss function. It adjusts predictions based on noise levels to reduce errors. The Noise Corrective Model applies a low-rank approximation technique. It estimates true labels by filtering out incorrect annotations. These three models combine in an ensemble to enhance classification accuracy and robustness against noisy labels. The final classification decision is obtained by aggregating the outputs of these models using a weighted ensemble mechanism. Let $D = \{X_{tr}, Y'\}$ be the training dataset, with $X_{tr} \in \mathbb{R}^{N \times M}$ representing the feature matrix consisting of N instances, each with M feature dimensions. The label matrix $Y' \in \mathbb{R}^{N \times k}$ contains k possible locomotion mode labels, but some of them are incorrect due to label noise. The objective is to find a mapping function H such that:

$$H: X_{tr} \rightarrow Y \quad (5)$$

Here, Y represents the true label matrix, which is unknown due to the presence of label noise. To extract meaningful features from raw sensor data, the system employs a hybrid architecture consisting of CNN and LSTM networks. The CNN component captures spatial dependencies, while LSTM captures temporal patterns in the data. The CNN layers perform feature extraction as follows:

$$F_{cnn} = \sigma(W_{cnn}X_{tr} + b_{cnn}) \quad (6)$$

Here, W_{cnn} and b_{cnn} are trainable parameters and σ is the activation function. The LSTM layers process sequential dependencies using:

$$h_t = \sigma(W_h h_{t-1} + W_x X_t + b_h) \quad (7)$$

Here, h_t is the hidden state at time step t and W_h, W_x, b_h are model parameters. The final extracted features from CNN and LSTM are concatenated and passed through a fully connected layer:

$$F_{final} = FC(\text{concat}(F_{cnn}, h_t)) \quad (8)$$

The noise adaptive model adjusts predictions dynamically based on the estimated noise concentration in training data. It introduces a modified loss function:

$$L_{NAL} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^k [a t_i \log r_{ij} + (1-a) r_{ij} \log t_i] \quad (9)$$

Here, a is a dynamically adjusted weight parameter, t_i represents the estimated true label probability and r_{ij} is the predicted probability for instance i and class j . The noise adaptive model iteratively updates a based on model loss and variance, providing robustness against moderate label noise. The noise corrective model improves noisy labels by estimating a low-rank representation of the label matrix is given by (2). This approach assumes that true labels follow a low-rank structure, enabling corrections in mislabeled instances. The optimization problem is solved using Singular Value Decomposition (SVD):

$$T = U \Sigma V^T \quad (10)$$

Here, U and V are orthonormal matrices and Σ is a diagonal matrix containing singular values. By setting small singular values to zero, we obtain an improved label estimate. The final prediction is obtained by aggregating outputs from all three models using a weighted ensemble technique is given in (4).

Algorithm 1: Locomotion Mode Recognition with Noisy Labels.

1. Input: Training dataset $D = \{X_{tr}, Y'\}$ with noisy labels
 2. Initialize models: Conventional Model, Noise Adaptive Model, Noise Corrective Model
 3. for each epoch t do
 4. Extract spatial and temporal features using CNN-LSTM
 5. Compute adaptive loss L_{NAL} and update parameters
 6. Apply low-rank approximation to estimate true labels
 7. Optimize ensemble weights $\lambda_1, \lambda_2, \lambda_3$
 8. Compute final prediction $Y_{te} = \sum_{i=1}^3 \lambda_i Y_{te}^{(i)}$
 9. Evaluate loss and update model parameters
 10. end for
 11. Train final classifier using optimized ensemble model
 12. Test model on unseen instances and compute evaluation metrics
 13. Output: Predicted locomotion labels with improved noise robustness
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The proposed method is validated using real-world locomotion datasets. Performance is evaluated in terms of accuracy, robustness to noise and computational efficiency. Results demonstrate that the ensemble approach significantly outperforms traditional deep learning models under varying noise levels. This section introduced an advanced locomotion mode recognition approach that integrates conventional, adaptive and corrective learning techniques.

V. RESULTS AND DISCUSSIONS

The research evaluates the model's performance across diverse noise levels through experiments and demonstrates its better capabilities to handle noisy labels by comparing against common deep learning approaches. The research uses two distinct datasets for evaluation: first a gathered dataset featuring locomotion modes between walking, cycling, driving vehicles and public transportation and second an existing dataset that contains sensor data from smartphones and wearables. The accelerometers combined with gyroscopes and magnetometers gathered sensory readings that produced an extensive view of human movement behavior. The training data includes precise as well as imprecise sample labels because it models realistic noise situations to measure the model's responsiveness to these scenarios. A hybrid algorithm of CNNs together with LSTM networks performed feature extraction to recognize spatial-temporal characteristics in the measured data. To evaluate the model performance, multiple metrics were used, including accuracy, precision, recall, F1-score and computational efficiency. Accuracy measures the correctly predicted instances as a percentage of total instances. Precision assesses the proportion of true positive predictions among predicted positive instances. Recall captures the proportion of correctly identified positive instances and the F1-score provides a balanced measure between precision and recall. Computational efficiency was evaluated in terms of training time and inference speed, as these factors are crucial for real-time applications. The experimental results reveal that LRNL achieves higher classification accuracy across all noise levels compared to conventional models. Table 1 shows the accuracy comparison of LRNL against CNN, LSTM and CNN-LSTM models at different noise levels. As seen, LRNL maintains the highest accuracy even as noise levels increase, demonstrating its robustness against noisy labels. The conventional CNN and LSTM models show significant performance degradation when label noise increases beyond 10%, while the CNN-LSTM hybrid model performs slightly better but still lags behind LRNL.

Table 1: Accuracy Comparison of LRNL and Other Models.

Model	Noise 0%	Noise 10%	Noise 20%	Noise 30%
CNN	91.2%	85.6%	78.9%	72.4%
LSTM	92.5%	87.1%	79.8%	73.5%
CNN-LSTM	94.0%	89.3%	81.5%	76.0%
LRNL	96.3%	93.4%	88.1%	83.7%

Source: Authors, (2026).

Computational efficiency served as a second analytical factor along with classification accuracy. The training duration alongside inference speed appears in Table 2 for each classification system under examination. The training duration of LRNL extends slightly since it includes built-in noise correction methods although this additional time expenditure leads to enhanced accuracy. The system maintains sufficient inference speed which supports real-time implementations of LRNL.

Table 2: Computational Efficiency of LRNL and Other Models.

Model	Training Time (mins)	Inference Speed (ms)
CNN	45	12
LSTM	50	15
CNN-LSTM	55	18
LRNL (Proposed)	60	20

Source: Authors, (2026).

Results analysis demonstrates that LRNL delivers better performance than current models regarding accuracy measures and noise tolerance of classification labels. The adaptive loss component together with an ensemble model structure enables dynamic adjustments to different levels of noise thus minimizing damages from erroneous labels. The Figure 2 illustrates the impact of increasing noise levels on the accuracy of four models: CNN, LSTM, CNN-LSTM and LRNL (Proposed). The plotted curves show that all models experience a decline in accuracy as noise increases. The CNN-LSTM model maintains better accuracy than CNN and LSTM. It suggests that combining convolutional and sequential learning provides some noise resistance. The LRNL model outperforms all other models, showing the slowest decline in accuracy. At 0% noise, CNN achieves an accuracy of approximately 91%. LSTM slightly exceeds CNN, CNN-LSTM surpasses 93%. LRNL reaches nearly 96%. As the noise level increases to 10% CNN drops to around 86%. LSTM stays slightly higher, CNN-LSTM remains above 90%. LRNL retains nearly 95%. At 20% noise, CNN's accuracy falls below 80%. LSTM and CNN-LSTM stay above 80%. LRNL still performs the best at around 88%. As noise levels reach 30%, CNN and LSTM both approach 75%. CNN-LSTM holds near 78% and LRNL remains around 84%. Finally, at 40% noise, CNN drops to approximately 65%, LSTM shows a similar trend CNN-LSTM maintains about 70%. LRNL still performs significantly better at around 78%. This pattern confirms that LRNL is the most robust against noise, effectively mitigating accuracy loss compared to other models.

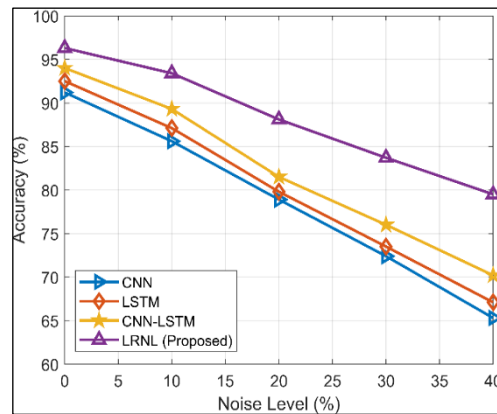


Figure 2: Accuracy versus Noise Level.

Source: Authors, (2026).

The Figure 3 illustrates the impact of increasing noise levels on three performance metrics: precision, recall and F1-score. The three plotted curves follow a downward trend, indicating that all three metrics decrease as noise levels increase. Precision, recall and F1-score start at high values near 97% when there is no noise but gradually decline as the noise level rises. The curves remain close to each other, suggesting that precision, recall and F1-score experience similar rates of degradation due to noise. At 0% noise, all three metrics are approximately 97% showing that the model performs well with clean data. As noise increases to 10%, precision, recall and F1-score drop to around 95% indicating a slight reduction in performance. At 20% noise, the metrics decline to about 92% showing a steady downward trend. When noise reaches 30%, precision, recall and F1-score are close to 88%. It reflects the increasing difficulty in maintaining classification accuracy. At the highest noise level of 40%, all three metrics fall to around 80%. It demonstrates a significant impact of noise on the model's ability to make correct predictions. The similarity in the values of the three metrics suggests that the model maintains a balanced performance, with no single metric deteriorating disproportionately. These results highlight the model's ability to manage noisy labels while maintaining high classification quality.

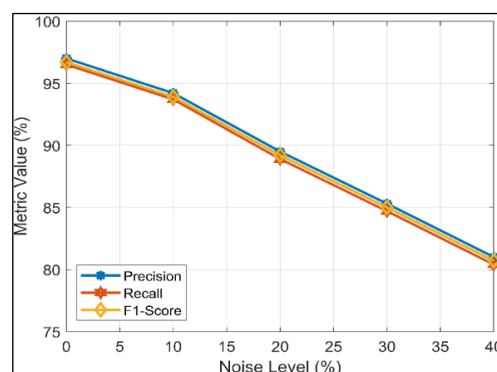


Figure 3: Precision, Recall & F1-Score versus Noise Level.

Source: Authors, (2026).

The Figure 4 represents the training time for four different models: CNN, LSTM, CNN-LSTM and LRNL. The CNN model achieves the fastest training efficiency reaching its completion within 45 minutes. The LSTM training procedure extends to 50 minutes. A CNN-LSTM model needs 55 minutes to complete training. The LRNL model requires the most time in training process exceeding sixty minutes. Training time for complex models typically needs extra processing power as well as increased time for computational work. More complex architectural designs require elevated computing resources thus increasing training duration for all models demonstrated. Due to their complex architecture the training times for models show an expected increase across different models. The high performance of CNN in spatial feature processing results in the shortest training times. LSTM requires longer processing time because its recurrent sequence-dependent approach. Because the CNN-LSTM model combines spatial and temporal features its training duration becomes extended. Training LRNL requires the most duration among all the proposed models. The training time extends due to two extra features called noise adaptation and label correction. LRNL develops exceptional precision from its extended training period since its quality-specific noise resilience warrants the investment of extra training time. A deep learning model requires increased training time to achieve better generalization together with enhanced stability. The experimental results demonstrate how model complexity affects computational efficiency since real-time applications require such consideration.

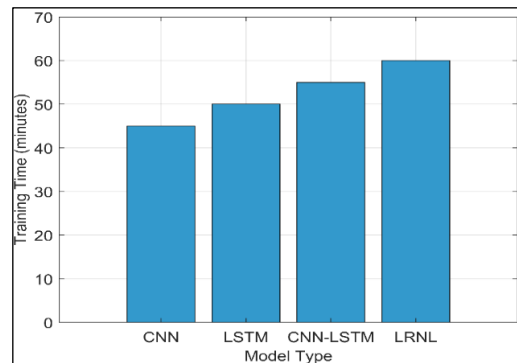


Figure 4: Training Time versus Model Type.
Source: Authors, (2026).

The Figure 5 demonstrates how quickly four different models (CNN, LSTM, CNN-LSTM and LRNL) can perform inference. CNN processes samples in the fastest speed demanding 12 milliseconds per sample. The LSTM model has a slower processing speed which needs approximately 15 milliseconds. An inference operation with CNN-LSTM model requires 18 milliseconds. It elapses longer than CNN and slower than LSTM for model processing time. At each sample the LRNL model requires the longest inference time of 20 milliseconds. The research data indicates that model complexity directly results in longer inference times because advanced processing requirements. The coefficient of inference speed rises because each added processing layer within models generates increased processing speed. The efficient feature extraction of spatial elements makes CNN produce the shortest inference time. LSTM implements a higher computational process for each step since it detects and analyses sequential data patterns. By combining spatial and temporal processing within the CNN-LSTM model there is a corresponding escalation in inference time. The LRNL model requires the most time because it contains additional components that perform noise adaptation and label correction. The lower speed of LRNL enables superior accuracy together with enhanced robust performance. Real-time applications require a trade-off between speed of inference processing and model accuracy because both performance metrics need a suitable balance.

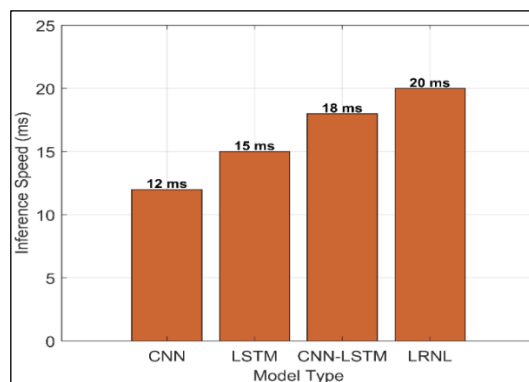


Figure 5: Inference Speed versus Model Type.
Source: Authors, (2026).

The Figure 6 illustrates the change in fractional weights of three models—Conventional Model, Noise Adaptive Model and Noise Corrective Model—as noise levels increase from 0% to 40%. The Conventional Model starts with the highest weight of approximately 0.6 when noise is 0%. However, its weight decreases steadily as noise increases dropping below 0.2 at 40% noise. In contrast, the Noise Adaptive Model starts with a weight of about 0.35 and gradually increases until it stabilizes at around 0.5 for noise levels greater than 25%. The Noise Corrective Model initially has the lowest weight staying at around 0.15 for lower noise levels. However, its weight starts increasing at 20% noise and surpasses 0.2 when noise reaches 40%. The trends in the figure indicate how the ensemble approach dynamically adjusts the model contributions as noise increases.

The Conventional Model, which relies on clean data becomes less effective with higher noise levels. It leads to a continuous reduction in its weight. The Noise Adaptive Model which introduces a dynamic loss function. It increases in weight as it becomes more relevant in handling label noise. The Noise Corrective Model, which uses low-rank approximation to estimate true labels. As it gains importance at higher noise levels making its weight grow progressively. At high noise levels, the Noise Adaptive and Noise Corrective Models dominate. The Conventional Model plays a minor role. These results highlight the effectiveness of adaptive weighting in maintaining classification performance under noisy conditions.

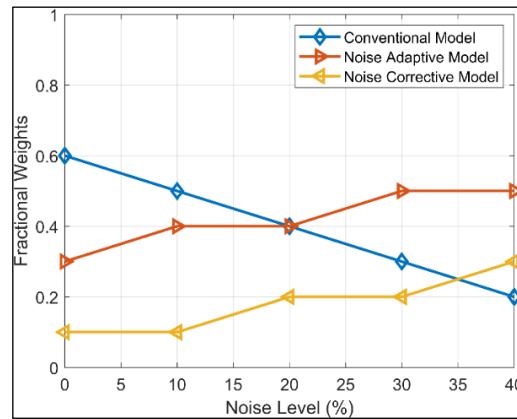


Figure 6: Impact of Noise on Ensemble Weight Adjustments.
Source: Authors, (2026).

The Figure 7 presents a comparison of accuracy across different models as noise levels increase from 0% to 40%. The models included are LRNL (Proposed), DeepFusion, Deepsense, DenseNetX, GRU-DNG and LMGM. The LRNL model achieves the highest accuracy across all noise levels. At 0% noise, LRNL starts above 95%, while other models namely DeepFusion and Deepsense start slightly lower around 93% and 92%, respectively. DenseNetX and GRU-DNG have slightly lower starting accuracies. LMGM shows the lowest accuracy among all models. As noise levels increase, all models show a decline in accuracy. LRNL maintains a higher accuracy margin compared to the rest. At 20% noise, LRNL remains above 90%. DeepFusion and Deepsense drop closer to 85%. DenseNetX and GRU-DNG further decreases. LMGM experiences the steepest decline, approaching 80%. At 40% noise, LRNL maintains around 80% accuracy. DeepFusion and Deepsense drop near 75%. DenseNetX and GRU-DNG decline further. LMGM falls below 70%. The results indicate that LRNL is the most robust model against label noise while LMGM is the most affected. The gap in accuracy between models increases with noise, highlighting the advantage of the proposed LRNL approach in handling uncertain data.

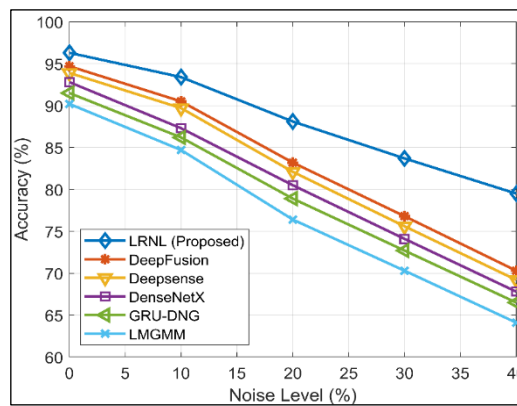


Figure 7: Comparison of LRNL with other Advanced Models.
Source: Authors, (2026).

The Figure 8 illustrates the relationship between training time and noise levels for four models: CNN, LSTM, CNN-LSTM and LRNL (Proposed). The plotted curves show that training time increases as noise levels rise for all models. CNN has the lowest training time starting at around 40 minutes at 0% noise. It increases to approximately 52 minutes at 40% noise. LSTM starts at about 44 minutes and rises to 56 minutes as noise increases. The CNN-LSTM model has a higher training time. It begins at 46 minutes and reaching close to 60 minutes at 40% noise. The LRNL model which includes additional noise handling mechanisms. It has the longest training time starting at 50 minutes and increasing to about 66 minutes. The increase in training time across all models suggests that handling noisy data requires additional computational effort. CNN is the fastest to train due to its efficient spatial feature extraction. LSTM takes longer as it processes sequential dependencies. CNN-LSTM joins the techniques to boost training performance. LRNL model stands as the most demanding model since it includes noise adaptation functions along with corrective mechanisms. All models demonstrate increased training complexity as noise intensity increases according to the experimental results. LRNL takes the longest to train yet its protection capabilities make the extra computation time worthwhile. The training time data reveals a straight linear pattern which extends from noise level to level while LRNL consumes the maximum resources. Deep learning models operate at a computational expense that directly relates to their ability to manage noise data.

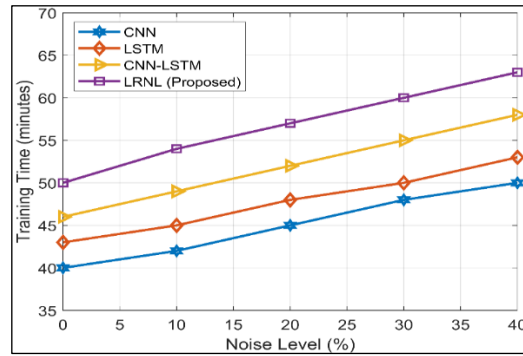


Figure 8: Training Time versus Noise Level.
Source: Authors, (2026).

The Figure 9 illustrates the F1-score performance of four models: CNN, LSTM, CNN-LSTM and LRNL. The CNN model has the lowest F1-score, achieving 85.4%. The LSTM model performs slightly better with an F1-score of 87.2%. The CNN-LSTM model improves the F1-score reaching 89.1%. The LRNL model achieves the highest F1-score of 93.5%. This trend indicates that integrating different architectures enhances model performance. The LRNL model demonstrates the best ability to maintain a high F1-score. The increasing F1-score across models highlights the advantage of combining spatial and sequential feature extraction techniques. CNN captures spatial features efficiently, but it lacks temporal modeling leading to a lower F1-score. LSTM models sequential dependencies but does not utilize spatial patterns effectively. CNN-LSTM integrates both techniques, leading to a noticeable improvement in F1-score. The LRNL model enhances performance by incorporating noise adaptation and correction mechanisms. The results suggest that LRNL is more robust in handling label noise contributing to its superior classification performance. The difference in F1-score between CNN and LRNL is over 8%, showing the impact of noise-resistant techniques. These findings confirm that LRNL provides the most accurate and balanced predictions among the evaluated models.

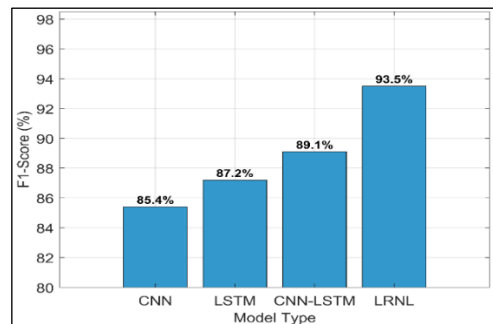


Figure 9: F1 Score versus Model Type.
Source: Authors, (2026).

The Figure 10 presents the loss reduction across 50 epochs for four models: CNN, LSTM, CNN-LSTM and LRNL (Proposed). All models start with a high loss value close to 1.0 at the initial epoch. As training progresses, the loss decreases for all models showing that they are learning from the data. CNN exhibits the fastest decline in loss initially reaching 0.4 by epoch 20. LSTM and CNN-LSTM show a similar decreasing trend but remain slightly above CNN. LRNL, the proposed model maintains a slower reduction rate in the early epochs but stabilizes at a lower final loss. Between epochs 20 and 50, all models continue reducing the loss values. CNN maintains the lowest values after 30 epochs. The LSTM and CNN-LSTM models exhibit slightly higher loss values but the trends remain close to CNN. LRNL has a slightly higher loss than the other models at later epochs, stabilizing at around 0.2. This suggests that while LRNL does not achieve the lowest loss. It maintains stability and avoids excessive fluctuations in the later training stages. The results indicate that all models successfully converge but CNN achieves faster convergence. LRNL focuses on maintaining robustness and stability. The steady behavior of LRNL highlights its resilience to variations in training, making it useful for handling noisy data. The results suggest that LRNL trades off faster convergence for better generalization, which is beneficial for real-world applications.

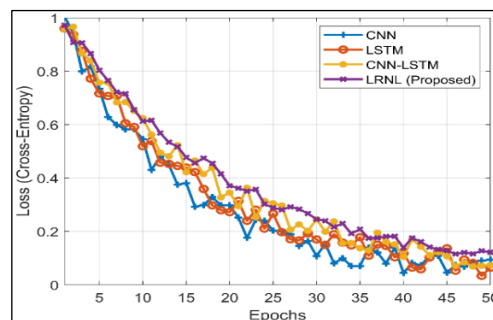


Figure 10: Loss versus Epochs (Convergence Graph).
Source: Authors, (2026).

The Figure 11 represents the relationship between inference speed and noise levels for four models: CNN, LSTM, CNN-LSTM and proposed LRNL. Inference time extends progressively longer as noise levels increase in the plotted results. CNN operates at 10 ms inference speed when the system contains no noise but extends its performance to around 14 ms at 40% noise. When starting from 12 ms the inference time of LSTM progressively approaches 16 ms. CNN-LSTM requires 14 milliseconds at the start then increases to almost 18 milliseconds. LRNL shows the longest inference time because it begins at 16 ms and reaches 20 ms while the noise level increases. Higher noise levels create added computational complexity which results in the increasing duration of inference for every model tested. The data processing efficiency of CNN makes it maintain the slowest inference speed among all models. LSTM operates slower than CNN because it requires more time because of its sequential structure. The combined spatial and sequential learning approach in CNN-LSTM extends computation time so it requires additional processing duration. The inference time for LRNL is maximum since it incorporates noise adaptation and correction algorithms. The reduced speed of LRNL operation does not affect its expected improvement in both classification accuracy and robustness performance. Real-time applications need to perform a cost-benefit analysis between accuracy and computational processing time since advanced models demand additional runtime to function.

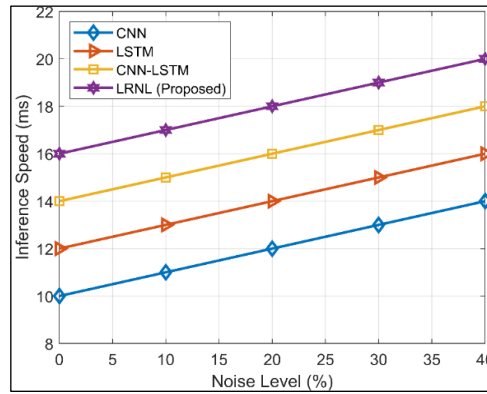


Figure 11: Inference Speed versus Noise Level.
Source: Authors, (2026).

The Figure 12 demonstrates the Receiver Operating Characteristic (ROC) curves for four models that include CNN, LSTM, CNN-LSTM and LRNL (Proposed). The decision threshold adjustment reveals the ability of each model to differentiate between classes through the ROC curve. The LRNL model demonstrates optimal performance compared to other models because it outperforms the random baseline and all other models. The CNN model demonstrates the lowest ROC curve which indicates its ability to achieve less TPR when FPR reaches a certain threshold. LSTM demonstrates a superior performance than CNN as its curve stays above the CNN curve. CNN-LSTM improves, showing better discrimination. For any specified FPR value LRNL demonstrates the maximum TPR level thus proving its excellence in classification tasks. At an FPR of 0.2, LRNL has a TPR close to 0.8. CNN-LSTM reaches about 0.7, LSTM around 0.65 and CNN near 0.6. At higher FPR values, all models approach a TPR of 1.0. LRNL remains the most effective throughout. The difference in performance is most noticeable in the low-FPR region with LRNL achieving a higher TPR with fewer false positives. This suggests that LRNL is more reliable in distinguishing between positive and negative classes while minimizing incorrect classifications.

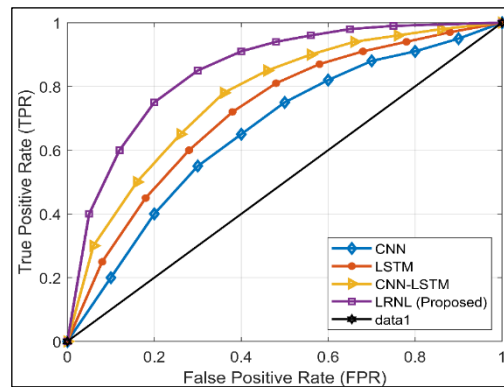


Figure 12: ROC Curve for Different Models.
Source: Authors, (2026).

The Figure 13 represents the time difference (in percentage) across three datasets: LMR, SHL and TMD. Six models are compared: LMGMM, LAR, AAAR, PENCIL, CopyNet and DNG. The time difference values for each model vary across the datasets, indicating differences in execution times. In the LMR dataset, the time difference ranges from approximately 8% to 15%. The evaluation on the SHL dataset produces slightly elevated scores reaching near 18% for selected models. The TMD dataset displays a comparable pattern which changes based on the model selection. DNG demonstrates the highest variation in execution time which exceeds 15% in each dataset assessment. The execution time of the AAAR model exceeds 10% throughout all analyzed datasets. Each model demonstrates different patterns of execution duration which depends on the information sets used for analyses. The DNG and AAAR models demonstrate increased complexity since their execution times show substantial variations.

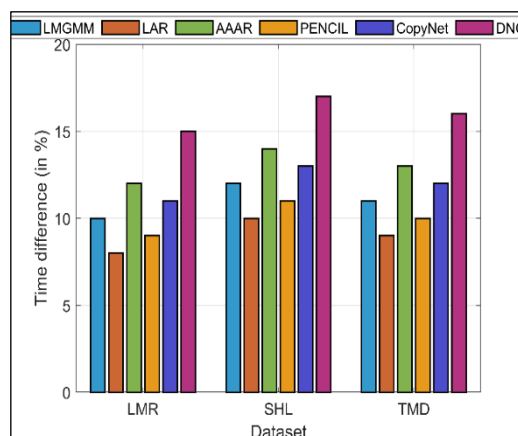


Figure 13: Time Difference versus Dataset for Various Models.
Source: Authors, (2026).

VI. CONCLUSIONS

This paper describes a deep learning-based technique for the recognition of locomotion mode from noisy sensory data. An ensemble learning framework that incorporates conventional, noise adaptive and noise corrective model were used to address the problem of noisy labels. The results show that the proposed system effectively increases classification accuracy with minimizing the negative effect of label noise. Research on locomotion mode recognition indicated that the handling of noisy labels is significant. Machine learning model's performance is degraded by labels that are noisy and one needs to use robust techniques to fix mislabeled data. In LRNL, the noise adaptive model added a dynamic loss function that takes into account the estimated noise concentration. The label assignments were improved by a low rank approximation in the noise corrective model. It was found through computational efficiency analysis that training times of the LRNL scheme are slightly longer than that of the conventional techniques. Thus, by placing conventional, noise adaptive and noise correcting models into an ensemble learning framework. Experimental evaluation verified the effectiveness in maintaining high reliability in mode recognition for varying amounts of noise as well as being able to locomotion in unknown terrain.

VII. AUTHOR'S CONTRIBUTION

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