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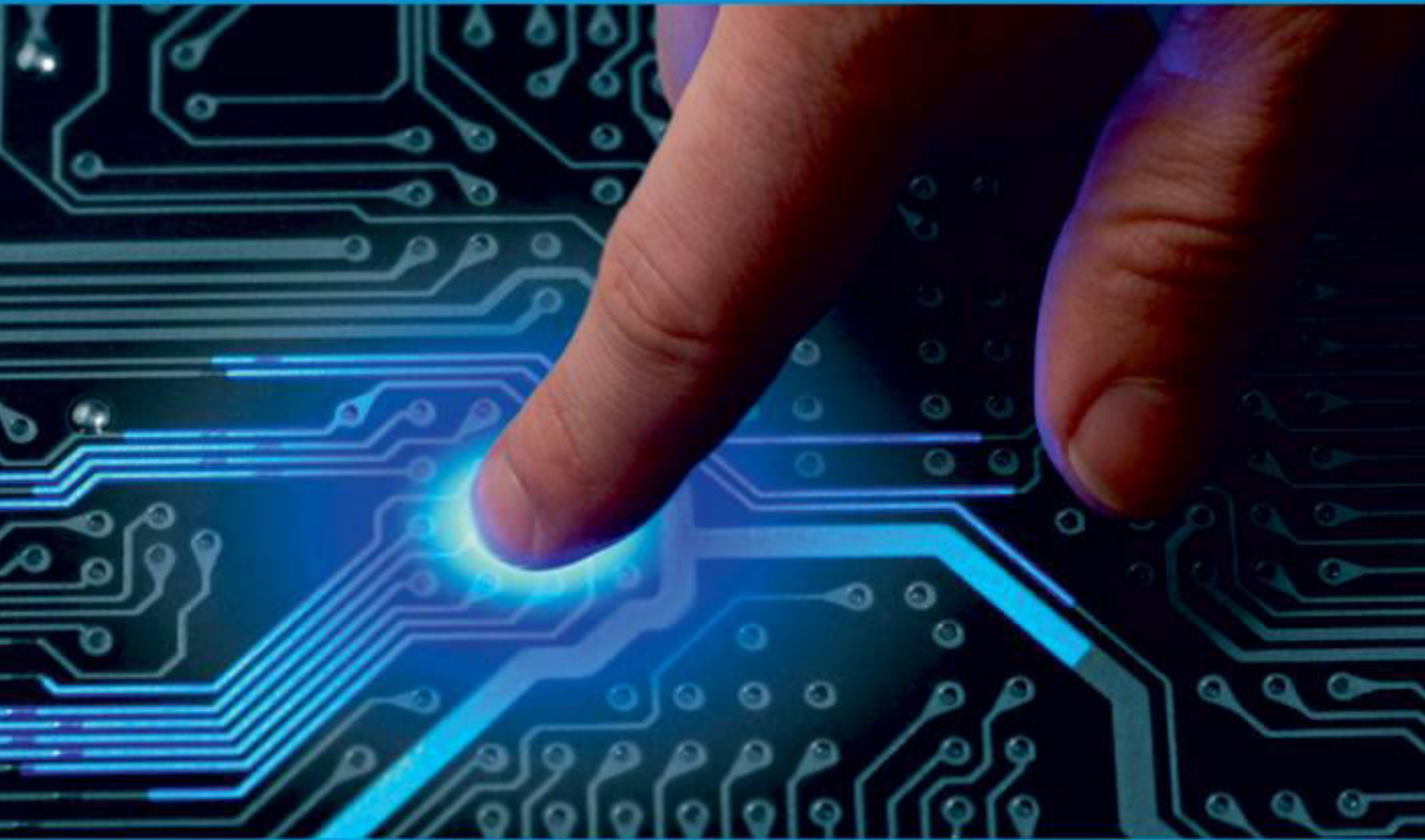

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A Convolutional Neural Network Approach for Multi-Class Tide Level Prediction

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ABSTRACT: Nodes in Mobile Ad Hoc Networks (MANETs) are limited battery powered. That's why energy efficient routing has become an important optimization criterion in MANETs. The conventional routing protocols do not consider energy of the nodes while selecting routes which leads to early exhaustion of nodes and partitioning of the network. This paper attempts to provide an energy aware routing algorithm. The proposed algorithm finds the transmission energy between the nodes relative to the distance and the performance of the algorithm is analyzed between two metrics Total Transmission energy of a route and Maximum Number of Hops. The proposed algorithm shows efficient energy utilization and increased network lifetime with total transmission energy metric.

KEYWORDS: Energy efficient algorithm; Manets; total transmission energy; maximum number of hops; network lifetime

I. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) consists of a collection of mobile nodes which are not bounded in any infrastructure. Nodes in MANET can communicate with each other and can move anywhere without restriction. This non-restricted mobility and easy deployment characteristics of MANETs make them very popular and highly suitable for emergencies, natural disaster and military operations.

Nodes in MANET have limited battery power and these batteries cannot be replaced or recharged in complex scenarios. To prolong or maximize the network lifetime these batteries should be used efficiently. The energy consumption of each node varies according to its communication state: transmitting, receiving, listening or sleeping modes. Researchers and industries both are working on the mechanism to prolong the lifetime of the node's battery. But routing algorithms plays an important role in energy efficiency because routing algorithm will decide which node has to be selected for communication.

The main purpose of energy efficient algorithm is to maximize the network lifetime. These algorithms are not just related to maximize the total energy consumption of the route but also to maximize the life time of each node in the network to increase the network lifetime. Energy efficient algorithms can be based on the two metrics: i) Minimizing total transmission energy ii) maximizing network lifetime. The first metric focuses on the total transmission energy used to send the packets from source to destination by selecting the large number of hops criteria. Second metric focuses on the residual batter energy level of entire network or individual battery energy of a node.

II. RELATED WORK

Baek et al. (2020) [1] developed a hybrid CNN-LSTM model to predict water levels and water quality parameters in South Korea's Nakdong River Basin. The CNN component modeled water levels, while the LSTM handled pollutants like total nitrogen and phosphorus. The model achieved high Nash–Sutcliffe efficiency values, indicating strong predictive performance. This approach effectively captured both spatial and temporal dynamics in hydrological data. **Yang et al. (2022)** [2] proposed an LSTM-based model for tidal level prediction, emphasizing the model's ability to learn temporal dependencies in tidal data. The study demonstrated that LSTM outperformed traditional statistical methods in capturing the nonlinear patterns of tidal fluctuations. The model's accuracy was validated using real-world tidal data, showcasing its applicability in coastal engineering. **Xu et al. (2022)** [3] introduced a hybrid model combining LSTM and non-stationary harmonic analysis for short-term tide level prediction in estuarine regions. The

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integration of harmonic components enhanced the model's ability to capture periodicities in tidal data. The approach yielded improved accuracy over standalone LSTM models, particularly in complex estuarine environments. **Li et al. (2022)** [4] presented the NEC+ model, a probability-enhanced LSTM framework designed to handle extreme events in time series prediction. By concurrently learning normal and extreme patterns, the model improved generalization across diverse hydrological scenarios. Evaluated on California reservoir data, NEC+ outperformed traditional LSTM models, especially in forecasting rare events. **Zhang et al. (2023)** [5] compared deep learning methods—MLP, LSTM, and attention-ResNet—for tidal current prediction. The attention-ResNet model achieved the highest accuracy, effectively capturing complex tidal dynamics. The study highlighted the potential of deep learning in enhancing tidal energy resource assessments.

Tan et al. (2022) [6] developed a CNN-LSTM model to predict dissolved oxygen levels in water bodies, a key indicator of water quality. The hybrid model leveraged CNN's feature extraction and LSTM's temporal modeling capabilities. Results indicated superior performance over traditional machine learning models, demonstrating the model's efficacy in water quality monitoring. **Xie et al. (2021)** [7] proposed a hybrid deep learning model combining wavelet transforms with LSTM networks for water level prediction in the Yangtze River. The wavelet transform decomposed the time series into multiple frequency components, enhancing the LSTM's ability to capture temporal patterns. The model outperformed conventional methods, offering improved accuracy in complex river systems. **Situ et al. (2023)** [8] introduced a CNN-RNN hybrid model with spatiotemporal feature fusion for urban flood prediction. By integrating spatial and temporal data, the model achieved high accuracy in forecasting flood events. Bayesian optimization was employed to fine-tune model parameters, further enhancing predictive performance. **Ghahfarokhi et al. (2024)** [9] conducted a comparative study of CNN-LSTM, LSTM, and 3D-CNN models for storm surge prediction in Tampa Bay. The CNN-LSTM model demonstrated superior generalization and robustness, particularly during extreme events like Hurricane Ian. The study underscored the importance of hybrid architectures in coastal hazard forecasting. **Feng et al. (2022)** [10] explored differentiable, learnable, regionalized process-based models with physical outputs for hydrologic prediction. By integrating neural networks with traditional hydrological models, the approach achieved accuracy comparable to state-of-the-art LSTM models. The framework provided interpretable predictions, bridging the gap between data-driven and process-based modeling.

Zhang et al. (2022) [11] proposed a CNN-BiLSTM model with an attention mechanism for water level prediction. The CNN extracted spatial features, while the BiLSTM captured temporal dependencies, and the attention mechanism highlighted important features. The model outperformed traditional methods, demonstrating enhanced accuracy in hydrological forecasting. **Dai et al. (2022)** [12] introduced an LSTM-seq2seq model for short-term water level prediction, leveraging sequence-to-sequence learning to capture temporal dynamics. The model achieved higher accuracy and faster convergence compared to traditional LSTM models. This approach proved effective in multi-step forecasting scenarios. **Muslim et al. (2021)** [13] investigated sea level prediction using machine learning models, including ANN and ANFIS, incorporating meteorological factors. The ANFIS model outperformed others, highlighting the significance of integrating environmental variables in sea level forecasting. The study emphasized the potential of hybrid models in coastal management. **Giaremis et al. (2024)** [14] applied LSTM-based machine learning for storm surge modeling, enhancing forecasting accuracy in coastal regions. The model effectively captured complex temporal patterns associated with storm surges. The study demonstrated the applicability of deep learning in improving coastal hazard predictions. **Ian et al. (2023) [15]** developed a bidirectional attention-based LSTM model to assess the risk of extreme storm surges under climate change scenarios. The model improved prediction accuracy by focusing on relevant temporal features. This approach provided valuable insights for climate adaptation strategies in coastal areas.

III. PROPOSED ALGORITHM

The proposed system aims to classify tidal water levels into three categories—low, medium, and high—using a 1D Convolutional Neural Network (CNN). The raw dataset includes timestamped water level readings from multiple stations. Temporal features such as hour, day, and month are extracted from the datetime field to capture periodicity in tide behavior. The stationID feature is encoded to handle categorical station identifiers, and the Water_Level is discretized into three quantile-based classes to enable multiclass classification.

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Before feeding the data into the model, the features are standardized using **z-score normalization**:

$$z = \frac{x - \mu}{\sigma}$$

where x is the raw feature value, μ\muμ is the mean, and σ is the standard deviation. This ensures that the CNN processes input features with consistent scaling, improving convergence. The normalized features are reshaped into a three-dimensional input format suitable for the 1D CNN: (samples,timesteps,features)(samples, timesteps, features)(samples,timesteps,features), where each sample represents a timestamped observation and each feature is a normalized attribute.

The CNN architecture begins with a convolutional layer:

$$Y_i = \mathrm{ReLU}\left(\sum_{j=0}^{k-1} x_{i+j} \cdot \omega_j + b\right)$$

where x is the input, www are the learned filter weights, b is the bias, and k is the kernel size. This is followed by a **MaxPooling1D** layer to reduce dimensionality and extract dominant features. A **Dropout** layer helps prevent overfitting by randomly deactivating neurons during training. The extracted features are flattened and passed through fully connected layers. The final output layer uses a **softmax activation function** to classify each input into one of the three tide level categories:

$$\sigma(z)_j = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}} \text{ for } j = 1, \ldots, K$$

where K=3 (for low, medium, and high).

The model is trained using **sparse categorical cross-entropy** loss:

$$L = -\log(P_y)$$

where P_y is the predicted probability for the correct class label y. Model performance is evaluated using accuracy, confusion matrix, and precision-recall metrics. The model demonstrates moderate predictive capability, especially in distinguishing high tide levels, but misclassification is notable for medium levels, likely due to overlapping feature spaces.

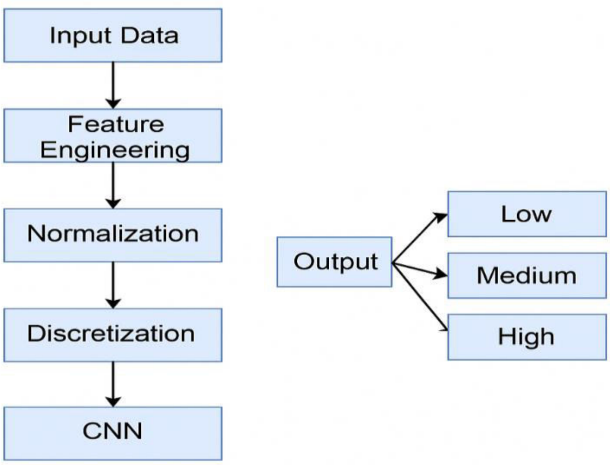

Fig 1 : Block Diagram of Proposed System

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IV. RESULTS AND ANALYSIS

The proposed CNN-based tide level classification system was evaluated using a comprehensive dataset containing timestamped tidal water level readings from various stations. After preprocessing, feature extraction, and normalization, the model was trained to classify the water level into three categories: Low, Medium, and High. The classification performance was assessed using metrics such as accuracy, precision, recall, and F1-score. The overall accuracy of the model on the test set was approximately **48%**, indicating moderate performance, with particular challenges in correctly classifying the Medium water level class.

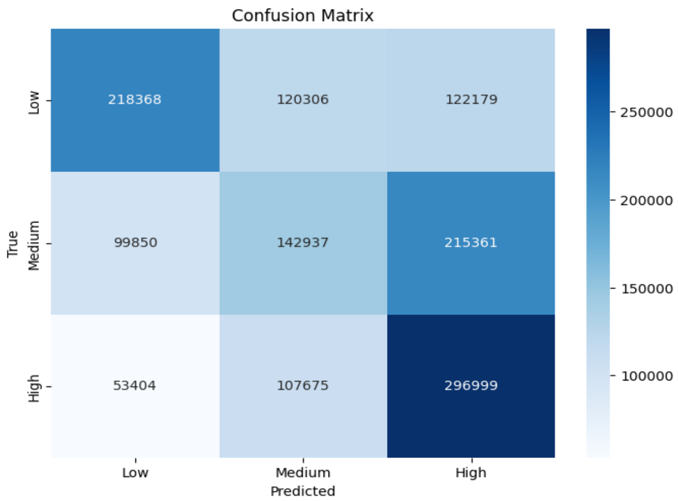

Fig 2 : Confusion Matrix

The **confusion matrix** offers deeper insight into the classification behavior of the model. For the "Low" class, the model correctly predicted 218,368 instances, but misclassified 120,306 as "Medium" and 122,179 as "High." For the "Medium" class, correct predictions were lower at 142,937, with a significant number misclassified as "High" (215,361). The "High" class had the best performance, with 296,999 correctly identified, though some were still predicted as "Low" (53,404) and "Medium" (107,675). These results indicate a tendency of the model to bias toward the High class, possibly due to overlapping feature patterns or imbalance in class distributions.

The **classification report** further quantifies this observation. The "Low" class achieved a precision of 0.59 and recall of 0.47, while "Medium" had the lowest precision (0.39) and recall (0.31), highlighting its ambiguity in the feature space. The "High" class had the strongest performance with a recall of 0.65 and a balanced F1-score of 0.54. These values suggest the model is more confident in identifying extreme values (low and high) but struggles with the transitional "Medium" class. This could be improved by enhancing feature resolution, using a larger temporal window, or exploring alternative discretization strategies.

Class	Precision	Recall	F1-Score	Support
Low	0.59	0.47	0.52	4,60,853
Medium	0.39	0.31	0.34	4,58,148
High	0.47	0.65	0.54	4,58,078

Table1 : Classification Report

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From the confusion matrix, it is clear that misclassifications primarily occur between adjacent classes—Low ↔ Medium and Medium ↔ High—which is expected given the natural progression of water levels. Despite the moderate classification accuracy, the model shows promising potential for practical applications in tide prediction and alert systems. With further tuning, such as optimizing network depth or integrating temporal dependencies through LSTM layers, the model could deliver higher classification performance and reliability in real-world deployments.

V. CONCLUSION AND FUTURE WORK

In this study, a 1D Convolutional Neural Network (CNN) model was developed for the classification of tidal water levels into low, medium, and high categories based on temporal and station-specific features. The dataset was thoroughly preprocessed, including time feature extraction, label encoding, normalization, and discretization of continuous water level values. The CNN architecture, comprising convolutional, pooling, dropout, and dense layers, demonstrated an overall classification accuracy of approximately 48%. The model showed comparatively better performance in identifying low and high tide levels, while medium levels were frequently misclassified due to overlapping feature ranges.

The confusion matrix and classification report highlighted the challenge in differentiating medium tide levels, indicating a potential need for more distinct features or advanced modeling techniques. Despite these limitations, the model presents a promising approach for automating tide level categorization, which is vital for maritime operations, flood management, and coastal planning. The results validate the feasibility of applying deep learning to environmental time series classification problems.

Future work will focus on improving model accuracy and robustness. This includes exploring recurrent neural networks (RNNs) such as LSTM or GRU to better capture temporal dependencies, employing advanced feature engineering methods, and utilizing larger or more granular datasets. Additionally, data augmentation and ensemble learning approaches may enhance classification performance. Integrating geospatial data and real-time streaming input could further extend the model's utility for real-world tide prediction and alert systems.

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