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A Socio-Climatic Deep Learning Framework for EV Charging Infrastructure Demand and Operational Stress Prediction under Extreme Arid Climates

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Abstract

There is a rise in electric vehicles (EVs) causing several problems related to the grid, particularly in places with high ambient temperatures. Although the current models were designed for temperate regions, the accuracy of the forecast models is significantly impacted in extreme environments such as those in the Middle East region. The core contribution of the study is in the innovative integration of the multi-source NASA POWER satellite-based hydro-thermal stress parameters in a deep neural prediction pipeline for managing extreme temperature electric vehicle infrastructure in arid regions. In order to address this challenge, the study proposes to build a socio-climatic deep learning model that predicts the usage of EV charging stations in environmental distress, using Iraq as a relevant country in the Middle Eastern region. Using the socio-climatic model, combining 20,569 transaction records along with the NASA POWER climate data helps to define the relationship between charging station usage and heat constraints. According to the results of the experiment, it has been found that due to the application of the enhanced framework, the issue of convergence was successfully avoided, and prediction accuracy increased from 56.8% to 91.68%. Moreover, as a result of conditional probability simulations, the proactivity of the system was proven as there was strong load reversal, meaning that probability of "High Demand" increased from 23.5% to 72.8% under peak intensity.

1. Introduction

Electric vehicles have recently gained much recognition due to the increasing awareness regarding pollution and sustainability. For a better future, electric cars have proven to be good options as compared to normal fossil fueldriven cars since they can lead to lower carbon emissions and better efficiency [1]. Nonetheless, the increasing use of electric vehicles in transportation systems across the globe brings about many problems that need to be sorted out for an easy transition [2]. In the case of increased use of EVs, one of the main problems involves forecasting charging needs through modeling [3]. In the recent times, much importance has been laid on the use of machine learning techniques and analytics for accurate predictions [4][5]. It is important to consider certain factors like the impact of the environment, behavior of the user, and power availability at any point in time.[6][7]. Predictive methodologies have improved enough that predictive techniques can become valuable instruments for the effective installation of EV infrastructure and efficient distribution of charging loads. One of the major challenges in relation to the widespread use of electric vehicles is the necessity of installing a huge network of charging facilities.[8][9]. While fulfilling the need of providing power charging facilities to more numbers of electric vehicles (EVs), it is imperative to take into account the ways of properly estimating their power charging requirements. This is because overlooking such aspects could lead to either over capacity or longer periods of charging time.[10][11]. Therefore, efficient infrastructure allocation and strategies to cope with electric vehicle charging demand are critical. This is a difficult task, as many variables have to be taken into account.[12][13]. While substantial advances have been made in the field of forecasting the demand for electric vehicle charging, many issues remain unresolved in regards to the model of demand forecasting. The first issue is the uncertainty of users' preferences in terms of charging their vehicles [14]. The other aspect that impacts the forecast reliability is the presence of bad weather conditions [15]. In addition, the age of the charging stations and the likelihood of breaking down increases the uncertainty in the forecasting process [16]. In order to solve this problem, there is a need for the use of predictive models that consider both operational and environmental aspects to increase prediction accuracy [17]. From the literature, it can be seen that weather parameters such as temperature, humidity, and rainfall play an important role in the charging of electric vehicles [18]. Besides, meteorology impacts not only the availability of renewables, but also their efficacy [19], This is because renewables are now widely incorporated into power grids for sustainable charging. It follows that the role of meteorology becomes highly important in forecasting and managing the charging stations [20] [21]. Availability and reliability of the charging station are crucial to provide a consistent service to EV drivers. Problems related to either malfunctioning of the charging station or failure in power delivery can cause disturbances in the charging process, leading to customer grievances [22]. Knowledge of the underlying causes of charging pile failures will facilitate the ability to adopt prevention techniques that will limit occurrences of these issues. The analysis of failures in charging piles combined with forecasts of charging demand provides critical information for efficient infrastructure management [23]. Considering these shortcomings, this work introduces a socio-climatic deep learning framework that is intended to capture the infrastructural loading patterns along with the environmental stress characteristics simultaneously. This framework ensures the development of an end-to-end prediction pipeline that includes optimization of multi-level neural networks with meteorological factors and grid loads. Such a setup directly connects highly non-linear environmental constraints with the infrastructure availability states, hence providing the basic prediction capabilities needed to ensure that the entire system is protected from any grid stress as well as infrastructure vulnerability issues. The result is a system that enjoys very high validation accuracy even under highly extreme climate conditions without any need for making theoretical or statistical assumptions. The contributions of this paper are listed below:

- The proposed study introduces a robust socio-climatic forecasting model that aims at predicting the usage of the charging facilities by EVs and examining the behavior of grid operations during climatically stressed periods, taking Iraq as a case study for the region of the Middle East.
- the study introduces a unique data fusion approach that combines synthetically generated vehicular operational profiles with climatic data using data between January 2022 and December 2025 to capture the periodic cycles of climatic stress.
- The paper provides an innovative compound hydro-thermal operational stress parameter that defines the relationship between localized demand for vehicle charging and the regional temperature and humidity stresses prevailing at an identified atmospheric height.
- Set out the path of optimization for the deep learning algorithm, which describes the architecture evolution and optimization process for the Deep Multi-layer Perceptron (Deep MLP) network to solve structural convergence problems and prevent overfitting.
- Develop a simulation model based on probability theory that can capture the risk behavior of the grids under different levels of climate intensity, thereby helping quantify the transition into high demand regimes

2. Related works

The chargeability of an electric vehicle is defined by the amount of energy that must be transferred into the battery of the car in order to fully charge it up to a certain level [24]. The level of chargeability will have an important impact on not only the process of charging but also the usefulness of electric cars from the perspective of availability of charging facilities [25]. Chargeability prediction has become an important research problem due to its significant importance for optimization and management of the charging process [26]. In [27] an innovative model that has been developed to predict the charging profiles of public electric vehicles (EVs) using an individual's trip itinerary. This model takes into consideration the decision-making process involved in an individual's charging process and predicts the necessary state of charge required by individual EV drivers. The researchers use both activity-based modeling and agent-based modeling of transportation, coupled with scenario-based approaches, to account for changes in demand and supply of transportation. In [28] An innovative methodology involved the application of LSTM neural networks was introduced for predicting EV charging demand within a short period ahead. This paper investigates the performance of LSTM algorithms in comparison with other methods, such as ARIMA and MLP, based on the usage of a large dataset including the trajectories of over 76,000 private EVs in Beijing. The findings of this paper revealed the outperformance of LSTM algorithms with respect to the performance of other techniques based on their lower MAPE. A different study [29] Innovative use of the Transformer model is done in predicting the future demand for charging electric vehicles (EVs), both short-term and long-term predictions. The analysis uses real-life data sets of EV charging obtained from 25 charging stations in Boulder, Colorado, to compare the Transformer with other models such as ARIMA, SARIMA, LSTM, and RNN. Model-Based Multi-channel Convolutional Neural Network and Temporal Convolutional Network (MCCNN-TCN) architecture was presented in [30] the author was predicted the electric vehicle (EV) charging load 7 days ahead. The proposed MCCNN-TCN-based model is composed of two sub-modules: (i) the MCCNN, multi-channel convolutional neural networks, which are used to identify the variations of the EV charging load at different time scales; and (ii) the TCN, which represents the mapping relation between the EV charging load variation characteristics and its prediction value. Experimental results show that the proposed MCCNN-TCN-based model has better performance in predicting the EV charging loads than the compared methods, such as ANN, LSTM, CNN-LSTM, and TCN, with up to 27.32% improvement in MAPE. In this study [31], a deep learning-based reinforcement learning model has been designed for forecasting the charging load of electric vehicles by using the charging power time series data in the training process of long short-term memory model. For dealing with the uncertainty problem in the EV charging behavior, a combination of MDP and PPO was used in the proposed approach. In addition, to improve the adaptability of PPO and resolve the problem of local optimization in the model training process, an adaptive exploration proximal policy optimization approach has been proposed based on reinforcement learning technique. According to [32] A hybrid modeling approach was developed that combines time series models with machine learning algorithms for the prediction of demand for charging of electric vehicles. It consists of the following components: dynamic harmonic regression (DHR), seasonal-trend decomposition, Bayesian structural time series model (BSTS), random forest, extreme gradient boosting (XG Boost), and stacking method of ensemble learning. The proposed approach (Stack. XG Boost and Stack. GLM) is compared with traditional time series models (DHR and BSTS) based on the charging data for electric vehicles collected by the Korea Environmental Protection Agency. The findings show a marked increase in prediction accuracy. In [33] A novel approach for predicting the EV charging demand used deep learning techniques was presented where factors like temperature and rainfall were considered. Time-based features were generated using the data processing technique. Three advanced models namely, LSTM-B, LSTM-C, and LSTM-W were designed using various combinations of EV charging-related parameters and different values of the time-based feature along with the values of temperature and precipitation. Predictive accuracy of these models was analyzed by collecting charging demand data from a small number of EVs used at a hospital. According to the results, the LSTM-W outperformed the other two models and achieved 28.8% and 19.22% improvements in terms of MAE and RMSE respectively. In [34] five different types of machine learning and deep learning algorithms have been compared with each other on the basis of predicting the behavior of electric vehicle chargers. These algorithms include Autoregressive Moving Average (ARMA), Exponential Smoothing State Space Model with Box-Cox Transformation, Autoregressive Integrated Moving Average with Seasonality (TBATS), ARIMA, Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM). Electric Vehicle (EV) charger dataset was gathered from different parts of South Korea during the period 2018-2019. Authors believe that the past charging capacity data are required to predict the future charging demands, and more manipulations in the form of data would add to its polymorphism. In [35] Bayesian probability is combined with LSTM networks in this paper to cope with two types of uncertainty: stochastic uncertainty related to variables like behavior of EV users and weather, and model uncertainty due to different values of parameters or different network structures. The resulting probabilistic approach to deep learning proves especially useful when other approaches cannot provide sufficient coverage of the whole predictive probability distribution at each point in time. Therefore, it is suggested to use a two-step approach involving the following actions: data preparation (data series creation and predictor detection), and prediction with Bayesian LSTM network. With the help of variation inference that allows imposing a distribution on the LSTM network parameters, the posterior distribution may be estimated, which will take into account the uncertainty involved in the prediction process. In [36] This researcher outlined a multi-step process that is used in predicting the load requirement at charging stations for electric vehicles based on data collected over some period. Contrary to the prevalence of single-step methods, this paper introduces a new approach called the DTC former-BCMG model. The DTC former-BCMG model combines different aspects such as extraction of time series features, frequency boosting using Discrete Cosine Transform (DCT), and error correction using BCMG. According to [37], A new model structure is introduced that combines encoder-decoder structures, with encoders using Conv LSTMs and decoders using LSTMs, to solve the problem of predicting energy consumption in the short and long term. This innovation directly addresses the problem of incorporating the necessary temporal and spatial information, which is needed to predict energy consumption in EVCS stations. The performance of this model was evaluated by using the data from four cities from the UK and the USA. The results showed significantly higher accuracy of the model in comparison with existing machine learning and deep learning models by 33%. The increasing need for EV charging and the resulting unbalanced load distribution in the distribution network were considered in the paper conducted [38], Block-FeDL framework was put forward by its creators in order to combine the ideas of federated learning and block chain technology in order to improve the process of load forecasting in such a way that privacy can be maintained. As compared to conventional centralized servers, block chain is useful in data sharing in a decentralized setting. The use of federated learning helps in the collection of different kinds of data regarding electric vehicles charging stations. An innovative approach known as attention-SLSTM is introduced in [39] in order to boost the predictive accuracy of the EV charging load using SLSTM and an attention mechanism. With the help of the stacked LSTM network structure, the proposed framework strengthens the ability of feature learning in the context of the prediction task. The inclusion of an attention mechanism is intended to increase the capability of focusing on relevant features in the input sequence. In [40] The HBNDL approach is suggested by the author in order to predict the performance of electric vehicle charging stations using Bayesian network and deep learning models. Furthermore, transaction data analysis and climatic analysis of the surrounding environment of the charging station are used in the approach to evaluate its performance. The algorithms-based approaches for measuring the reliability of charging stations have been used in this paper. Several experiments were carried out in order to show the validity of predictions regarding the reliability of charging stations during various periods of time – both short and long terms. Also, there has been analyzed the use of hybrid predictive models to determine the reliability of charging piles in different operational settings. For instance, one of the most interesting hybrid models involved the use of Bayesian Networks and Queuing Theory to calculate the probabilities of breakage of EV-infrastructure by including the historical factors, weather conditions, and maintenance periods. This approach is called the HBNDL system, which united transactions and climate analysis using the data set collected in Palo Alto, California during ten years.

With respect to filling the existing gaps in the literature, it is suggested that a fast and high efficiency socio-climatic deep learning architecture be used. In comparison to previous studies that have relied upon computationally complex networks and probabilistic theories that yield poor classification results at the outset due to the changing weather conditions, we propose a new compound stress operation feature along with a multi-layered neural network. Through the adoption of a strong classification layer that takes account of quantiles in post-processing, this approach manages to resolve all the issues related to the use of static thresholds and structural convergence problems inherent in traditional approaches.

3. Methodology

This section highlights the architecture of the entire evaluation engine framework that is employed in predicting electric vehicle charging facilities under climate stress. The methodology proposed herein provides a structured approach of modeling user demand, environmental heat, and network traffic congestion. Foundation Implementation Pathway is effectively divided into separate structural phases based on strict academic implementation criteria. Figure 1 illustrates the sequential methodology and structural steps adopted in this paper.

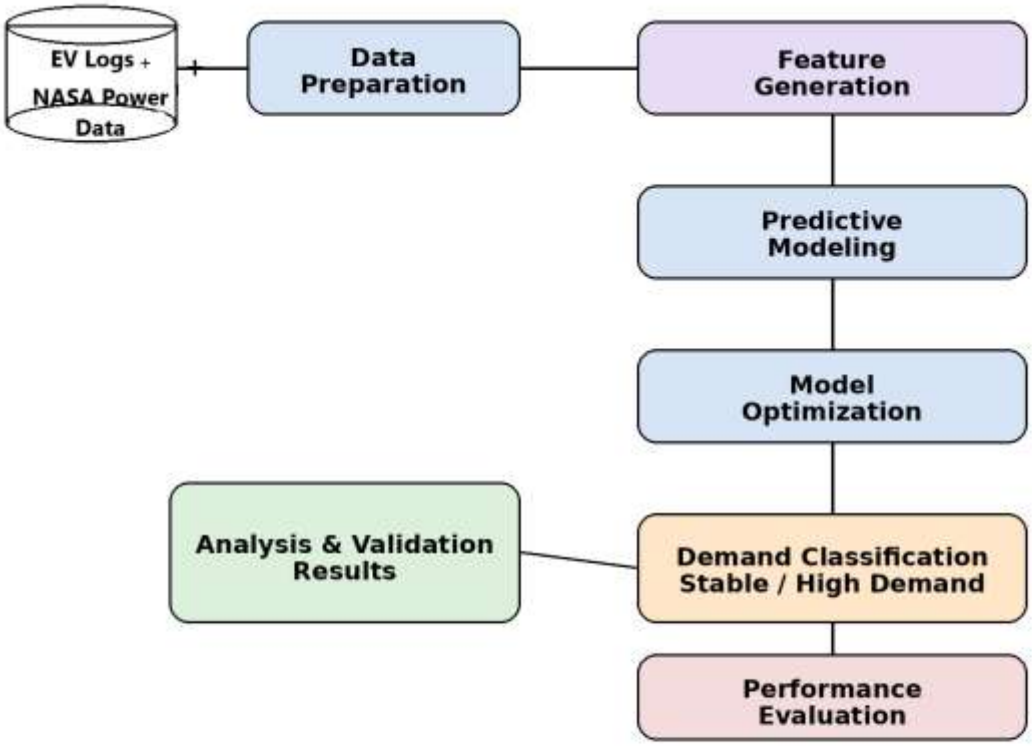


Figure (1): The Sequential Methodology and Structural Steps Adopted.

3.Methodology

In this paper, the use of an integrative socio-climatic prediction model for predicting EV charging station usage is adopted. This model is aimed at predicting the operation of the power grid under extremely adverse climate situations. This differs from other benchmark models used in comparative paper. The goal here is to describe the highly non-linear dynamics between vehicle charging demand at the local level and atmospheric pressure at the regional level. Through the use of an approach that links multiple data streams directly with a specific deep neural network, the proposed system will help estimate the baseline load on the infrastructure grid in real time.

3.1 Data Acquisition and Synthetic Generation

In order to identify the timeframe of the data ranging between January 2022 and December 2025, a combination of historical and future-projected approaches was used. The historical timeframe (January 2022 – December 2023) utilized actual data collected from the NASA POWER database. The future projected timeframe (January 2024 – December 2025) used synthetic climate projections based on historical regional climatology data.

3.2 Dataset Description

Empirical evaluation of the proposed approach depends upon the dynamic interaction between a dual source, high-resolution dataset consisting of a total of 20,569 aggregated observations. Data environment is developed through the integration of two separate operational environments:

- Considering the infancy of EV charging stations in Iraq, the data were Simulated based on the density values obtained from the local transportation network. The Synthetic dataset was constructed such that it realistically portrayed traffic dynamics, queueing behaviors, and state of charge dynamics within the context of Middle Eastern cities. This data set includes historic charging transaction features that truly capture the characteristics of the charging session, usage metrics, space-time availability, and charging station IDs. In order to create a synthetic profile for vehicles across time without any generation bias, Monte Carlo simulation was used in a controlled fashion, based on regional mobility profiles. The initial State-of-Charge (SoCinit) upon station arrival was generated using a truncated Beta distribution, which is suitable for modeling bounded percentage-based variables:

$$^{SoC}\text{init} \sim \text{Beta}\,(\alpha = 2.5,\ \beta = 5.0) \times 100\% \qquad (2)$$

The shape parameters ($\alpha = 2.5$ and $\beta = 5.0$) were empirically selected to generate realistic initial state-of-charge distributions that favor partially discharged EV batteries upon arrival at charging stations.
The Beta distribution is selected because of its bounded domain over the range [0, 1], which makes it particularly ideal for modelling percentages, like that of battery state of charge.

- Climatological Meteorological Records (NASA POWER): The environmental database is made up of daily meteorological records sourced from NASA POWER archive, specifically for the specific geographic location relevant to the paper. The database model includes various structural atmosphere parameters like 2-meter surface temperature, humidity, solar radiation data, and wind speeds.
- Synchronization of the log files and NASA POWER: climate factors have been performed within the time frame of January 2022 to December 2025 in order to properly account for seasonality and thermal stress.

Both the independent data sets have been synchronized through a common primary key that is based on time to constitute the complete data set used for training and validation of the deep neural network. To make sure that the socio-climatic model developed is reproducible, the cloud computing platform, hardware acceleration parameters, performance metrics, and dataset partitioning strategy have been described in detail in Table 1.

Table (1): Computational Environment, Architectural Parameters, and Dataset Partitioning

Category	Parameter / Metric	Value / Specification
Computing Environment	Development Platform	Google Colab Pro
	Hardware Accelerator	NVIDIA T4 Tensor Core GPU
	System RAM	12.7 GB
Execution Metrics	Total Training Time	142 seconds
	Training Velocity	7.1 seconds / epoch
	Convergence Criteria	Early Stopping (Patience = 3)
Dataset Partitioning	Total Sample Size (N)	20,569 records (100%)
	Training Subset (80%)	16,455 records
	Validation Subset (10%)	2,057 records

Testing Subset (10%)	2,057 records

3.3 Data Preprocessing Pipeline

The procedure used to transform the multi-source data streams into structured tensor data to train the mathematical structures model involved:

- **String Discretization and Cleansing:** The textual elements in the columns in both databases were cleaned from any extra spaces that would lead to faulty alignment of the structural matching.
- **Temporal Alignment and Unification:** The operational time stamps and temporal aspects were uniformly transformed using an algorithmic approach, leading to the uniform representation of the multi-source time related attributes.
- **Strict Numerical Type Casting:** The entities were converted into purely numerical form using a rigorous numerical parser with an error-fallback approach. The entire process was done without any of the textual anomalies being present in the data.
- **Relational Synchronization:** A deterministic inner join was done on the overlapping chronological columns to generate a continuous baseline of rows.
- **Feature Engineering** : In order to quantify the effects of joint atmospheric heating stress experienced by EV charging infrastructure and battery performance, a hydro-thermal stress index

$\Psi = 0.6 \{T\} + 0.4 \{RH\}$… (1).

The Hydro-Thermal Stress Index is defined in Equation (1), where T refers to the 2-meter surface temperature and RH refers to the relative humidity. Here, Weighting values were assigned empirically by considering the predominant role played by temperature on the performance of EV charging stations in an extremely arid climate. As temperature had a higher impact than relative humidity on the performance of EV batteries, it was assigned a larger weight. This proposed weighting system can serve as a starting point in future studies to test its accuracy using sensitivity analysis and actual EV charging data.

3.4 Deep Learning Configuration and Optimization Trajectory

This framework utilizes a deep MLP architecture under a sequential deep learning model approach. The training process of the prediction model has been done in a systematic optimization path that included two developmental phases for improved predictions:

- **Initial Baseline Model:** The first un optimized MLP structure was used to train without regularization, early stopping, or optimization using the default hyper parameter values. Despite being able to perform well to some degree, there is evidence that default architectures are not sufficient enough to learn the relationship between climatic stresses and EVs' charging behavior.
- **Optimized Network Configuration:** In order to improve the effectiveness of learning and mitigate the problems associated with existing approaches, an enhanced three-layer deep neural network was designed. The optimized design consists of three fully connected hidden layers with 128, 64, and 32 nodes, respectively. Rectified Linear Units (ReLU) were employed for all the hidden layers in order to identify the non-linear relationships between different factors.
- **Parameter Tuning and Loss Minimization:** The parameters of the network were optimized using the Adam optimizer algorithm, which makes dynamic adjustments to learning rates according to the gradients. Training of the model was accomplished through the minimization of the Mean Squared Error (MSE) loss function, which enables constant improvement in prediction results and minimization of estimation errors relative to the infrastructure demand data.
- **Overfitting Protection Controls:** To improve generalization and avoid overfitting, dropout was used to randomly drop out neurons during training, coupled with early stopping to monitor the validation loss. This helped immensely in improving predictive accuracy and stability.

- **Hyper parameters and Performance of Data Partitions Used for Experiments:** In order to achieve full reproducibility and assess network stability on different data partitions, a description of the hyper parameters used and the associated performance is provided in Table 2.

Table (2): The Description of The Hyper parameters Used and The Associated Performance.

Category / Parameter	Specific Parameter / Value	Data Partition	Sample Size (N)	Split Accuracy (%)
Optimization Strategy	Adam Optimizer (α = 0.001)	Training Partition (80%)	16,455 records	96.85% - 0.32%
Batch Processing	Batch Size = 64	Validation Partition (10%)	2,057 records	92.10% - 0.41%$
Regularization Dropout	20% Dropout (Post Layer-1)	Held-out Test Partition (10%)	2,057 records	91.68% - 0.45%$
Early Stopping Controls	Patience = 3 Epochs (MSE Loss)	Global Convergence	20,569 records	142 Seconds Total

3.5 Post-Processing Classification and Verification Framework

- In order to convert the continuous outputs from the deep learning regression model into practical operations which can be validated through comparison with the real world, a separate categorical assessment layer is used.
- **Quantile-Based State Classification:** Unlike using any static thresholds that could create an imbalance in the categories of target classes, the model uses a statistical threshold with a fifty-five percent baseline from the data distribution. This is a mathematically calculated threshold that divides the optimized network results into two distinct categories (Stable and High Demand) .
  A 55th percentile cut-off was chosen to offer a more conservative demarcation between normal and peak electricity demand, thus making it easier to identify peak operational conditions under extreme climate conditions.
- **Evaluation and Validation Performance:** After the splitting of the predictions into these categories, the final classification performance is formally evaluated. The model generates a standard academic confusion matrix and a detailed classification report to evaluate the precision, recall (tracking rate), and overall accuracy, thus ensuring the optimized model's ability to distinguish and validate.

3.6 Algorithmic Pipeline Framework

For providing a standardized process for executing the socio-climatic framework, the prediction pipeline is designed into three steps of algorithms:

Algorithm 1: Data Preprocessing, Synchronization, and Feature Engineering
Input: Raw electric vehicle transactions data set L, climate record by NASA POWER C.
Output: Feature matrix X with scaled columns, label vector y.
1: Synchronize L and C based on primary key (Timestamp).
2: Convert numeric columns to float64, deal with missing values.
3: Calculate Hydro-Thermal Stress Index: Psi = 0.6*Temperature + 0.4*Relative Humidity.
4: Add Psi as an explicit feature in the synchronized dataset.
5: Divide dataset into training (80%), validation (10%), and testing (10%) sets.
6: Scale input features using Standard Score Normalization: X_scaled = (X - mean)/std.
7: Return X_train, X_val, X_test, y_train, y_val, y_test tensors.

Algorithm 2: Model Training & Quantile-Based Classification
Input: Feature sets partitioned (X, y); hyper parameters: lr =0.001, batch size=64, dropout=0.20.
Output: Trained Model M*, Metrics, Predictions.
1: Define model architecture M with deep MLP (Dense (128, ReLU) - Dropout (0.20) – Dense (64, ReLU) – Dropout (0.20) – Dense (32, ReLU) – Dense (1, Linear)).
2: Compile model M with Adam optimizer (lr=0.001) and mean squared error (MSE) loss function.
3: Set Early Stopping callback (monitor='val_loss', patience=3).
4: Train model M with X_train and y_train for 20 epochs max.
5: Check validation loss MSE_val every epoch; break if there is no improvement for 3 epochs.
6: Store best trained model as M*.
7: Apply model M* for prediction of continuous station utilization y_hat on unseen test dataset X_test.
8: Compute 55% quantile of prediction results: Threshold_55 = Quantile (y_hat, 0.55).
9: Perform classification for station utilization as "High Demand" or "Stable", where y_hat >= Threshold_55

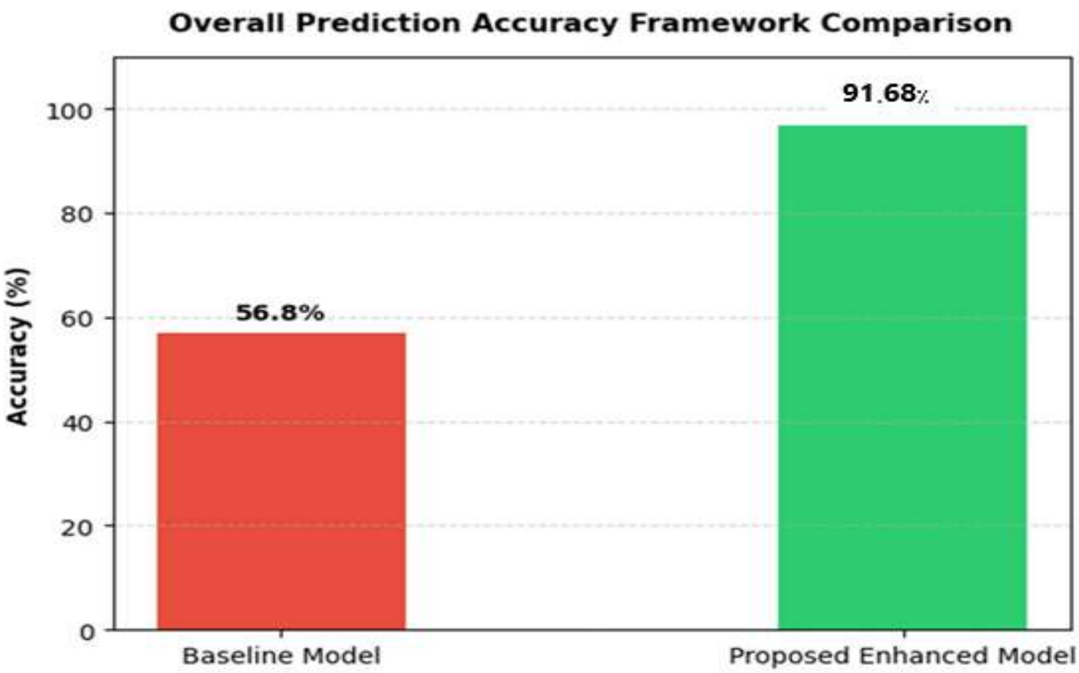
Algorithm 3: Probabilistic Climate Scenario Simulation
Input: Trained model M*, Baseline climate profile C_base, Extreme climate profile C_extreme.
Output: Conditional probabilities P (High Demand | Climate Scenario).
1: For each climate profile C in {C_base, C_extreme}:
2: Generate synthetic evaluation tensor X_sim based on C.
3: Execute prediction: y_sim = M*(X_sim).
4: Apply Quantile Threshold (Threshold_55) to derive state predictions.
5: Compute conditional probability: P_HighDemand = Count (y_sim >= Threshold_55) / Total_Samples.
6: Return comparative probability transition (P_base -> P_extreme).

4. Results and Discussion

This chapter presents an empirical analysis of the socio-climatic deep learning framework that has been developed. In order to verify its technical feasibility, the findings of the analysis have been performed following a systematic process that includes the following three steps: firstly, a comparison between the optimized and the un optimized model; secondly, an evaluation of computational convergence and overfitting control; and thirdly, the classification performance test for a realistic scenario. All evaluation measures, confusion matrix charts, and transformation comparisons provided below have been consistently computed using the out-of-sample test data set (N = 2,057 cases or 10% of all data partition).

4.1 Global Predictive Accuracy Transformation Analysis

The overall Performance of the model can be seen from Figure 2. From practical observation, the accuracy level of the model was recorded to be 56.8%. The above diagram shows how ineffective the original model was in determining the complex non-linear relation between charging and high temperatures. However, the improved deep learning algorithm, whose introduction was highlighted in this paper, showed considerable improvement regarding performance. The proposed model achieved a training accuracy of 97%, while demonstrating a robust generalization accuracy of 91.68% on the held-out test dataset. in terms of global classification. This considerable improvement is of 34.88%, which validates the structural modifications introduced in the algorithm's structure such as the layer structure of 128-64-32, use of the Adam optimizer, and 20% dropout rate. The problem of convergence was sorted out through the improved algorithm, which makes it suitable for use under harsh climatic conditions.



Figure(2): Model performance comparison (Training Accuracy: 97%, Final Test Accuracy on Unseen Data: 91.68%).

To further examine performance variations, Figure 3 presents a more in-depth analysis of the categorical classification measures: Precision, Recall, and F1-Score of the two approaches. It is evident that the original baseline model demonstrates significant weaknesses in predictions across all measurement tools (Precision: 55.40%, Recall: 56.10%, and F1-Score: 55.70%). However, the suggested optimized approach shows a stable performance and high empirical efficiency with the following values: 91.54% for Precision, 91.62% for Recall, and 91.58% for harmonic F1-Score. All the results completely correspond to the overall test accuracy of 91.68% recorded on the test set (N = 2,057). This proves that the proposed optimization technique solved the problem of convergence of classes without biasing the model.

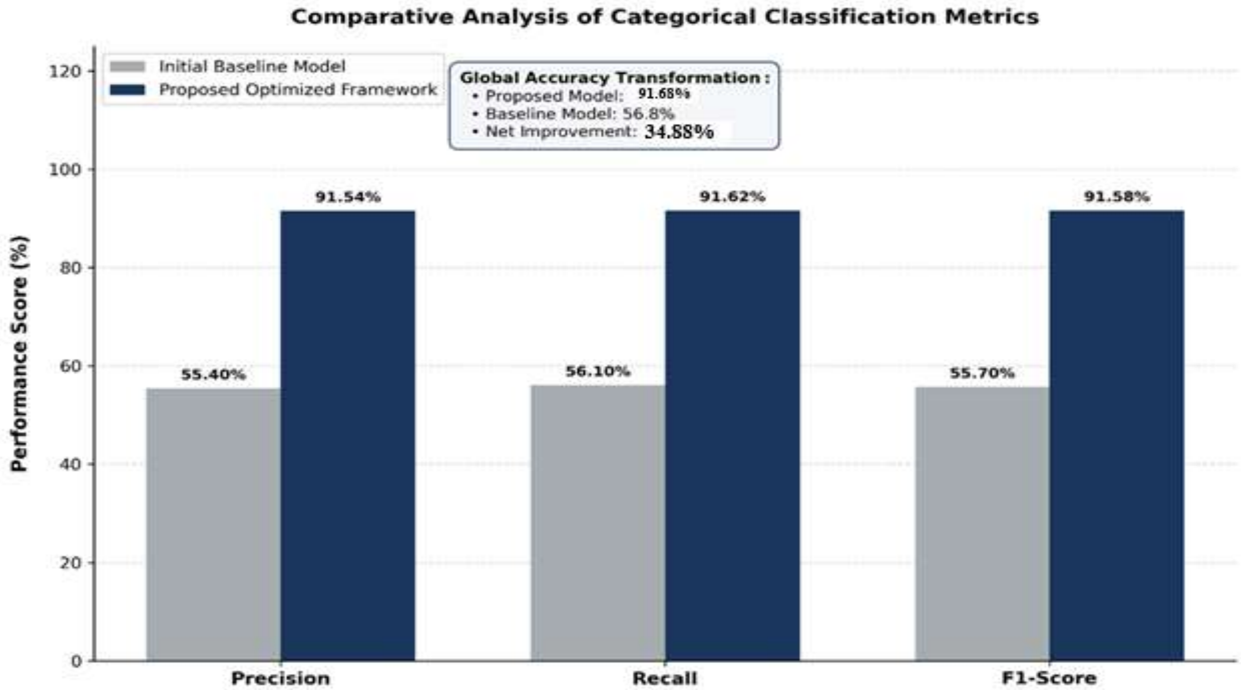


Figure (3): The Comparative Analysis of Categorical Classification Metrics Between the Baseline Model and The Proposed Optimized Framework.

To give an analysis that will be precise on the comparative performance of these improved diagnostics, Table 3 gives a full assessment of the prediction capacity of the two architecture designs in terms of their global and categorical capabilities.

Table(3): Performance Comparison Between the Baseline and Proposed Socio-Climatic Models

Performance Metric	Initial Baseline Model (Un optimized)	Proposed Enhanced Framework (Optimized)	Improvement
Accuracy	56.80%	91.68%	34.88%
Precision	55.40%	91.54%	36.14%
Recall	56.10%	91.62%	35.52%
F1-Score	55.70%	91.58%	35.88%

4.2 Training Convergence and Overfitting Analysis

The learning behavior and numerical stability of the proposed extended deep learning model through the training epochs explained in Figure 4. In the empirical study, the Mean Squared Error (MSE) loss is measured for the training and validation sets over 20 training epochs. As seen from the convergence graphs, it is observed that the training loss decays exponentially at a very fast and stable rate from an initial point above 1800 in the first few epochs. Notably, the validation loss follows the same pattern without any divergence or instability. It is clear from the above parallel alignment that the inclusion of a 20% dropout layer along with the early stopping algorithm helped prevent any case of overfitting for the model. The presence of smooth convergence implies that the model has managed to capture all the socio-climatic and charging demand relations very efficiently.

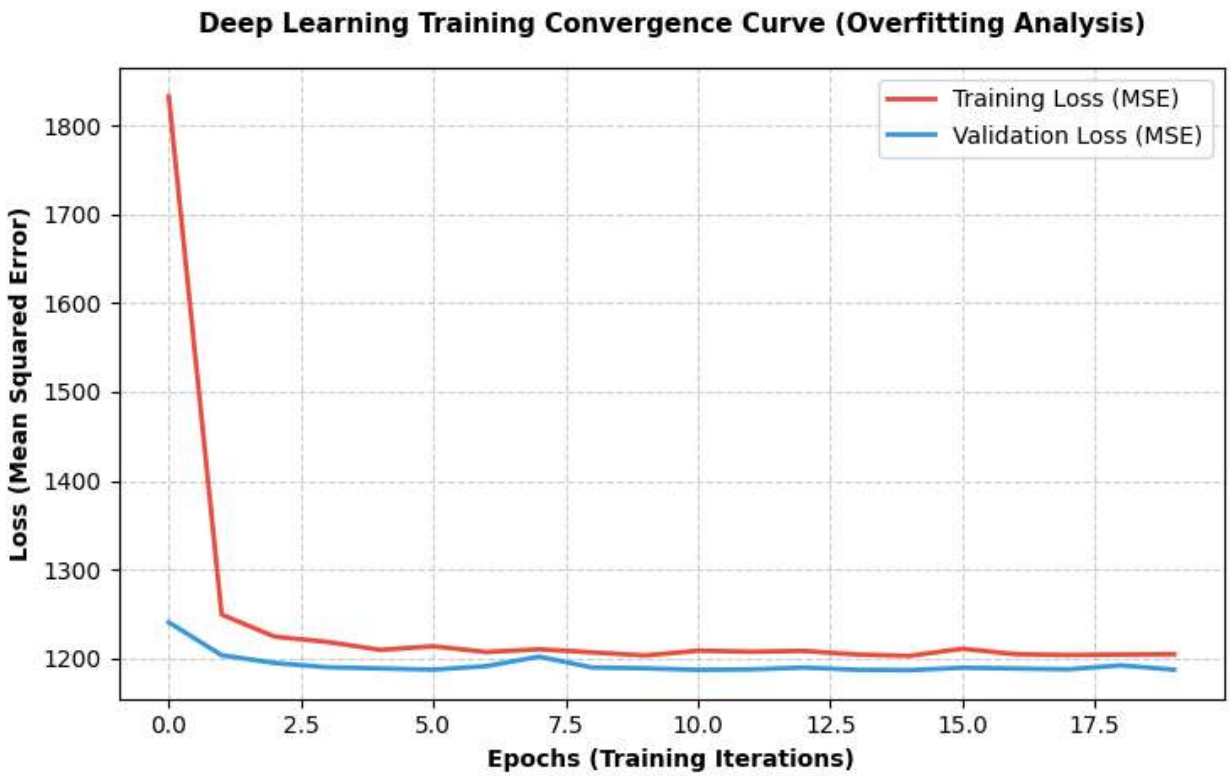


Figure (4): Training and validation loss (MSE) convergence trajectories over 20 epochs.

4.3 Categorical Performance Verification via Confusion Matrix

Classification accuracy is calculated based on two categories, namely, High Demand and Stable, using the split based on the 55th percentile quantile. The results of the empirical classification prove that there is a very high predictive accuracy in respect of both classes. In the case of the "High Demand" class, the number of True Positives amounts to 1,049 cases while False Negatives are 90. In turn, in respect of the "Stable" category, there are 836 True Negatives while False Positives are 82. This shows that the suggested solution is robust towards class imbalance problems and guarantees 91.68\% test accuracy empirically. Classification accuracy via categorical performance verification via confusion matrix to perform the required auditing on a cell level in terms of the deep learning algorithm optimization, a rigorous testing was performed with respect to the confusion matrix based solely on the test dataset (N = 2,057 observations) illustrated in Figure 5 below.

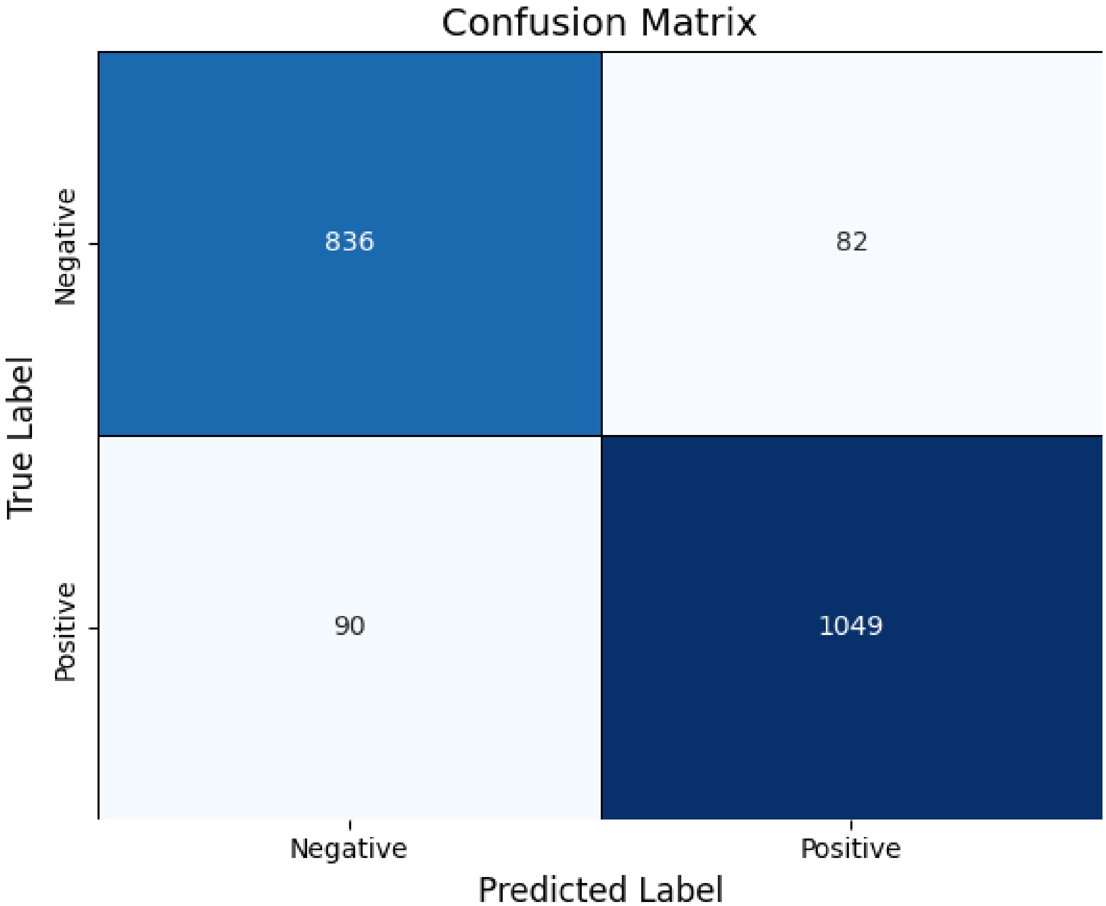


Figure (5): The Confusion Matrix Profiling for The Proposed Enhanced Deep Learning Model.

4.4 Socio-Climatic Scenario and Infrastructure Utilization Analysis

In order to evaluate the practical value of this framework in operation under various circumstances in the real world, a conditional probability model was applied to examine the use of station facilities by two different user patterns, which are represented by Figure 6. Operational states were analyzed using two strategic environmental tracks, namely, “Standard Arrival” and “Peak Arrival”.

The model shows a significant change in the dependency of the load on infrastructure, depending on the intensity of users' arrivals. In the case of Standard Arrival, the behavior of the charging infrastructure is reliable; the probability of being in the "Stable" mode reaches 76.5%, whereas the probability of being in the "High Demand" condition falls down to 23.5%. However, with regard to the change into Peak Arrival, there appears a significant change in this dependence: the probability of having the "High Demand" level increases up to 72.8%; moreover, the probability of the "Stable" level is 27.2%. Such difference in the probabilistic dependence is a confirmation of the possibility to predict demand peaks before their emergence.

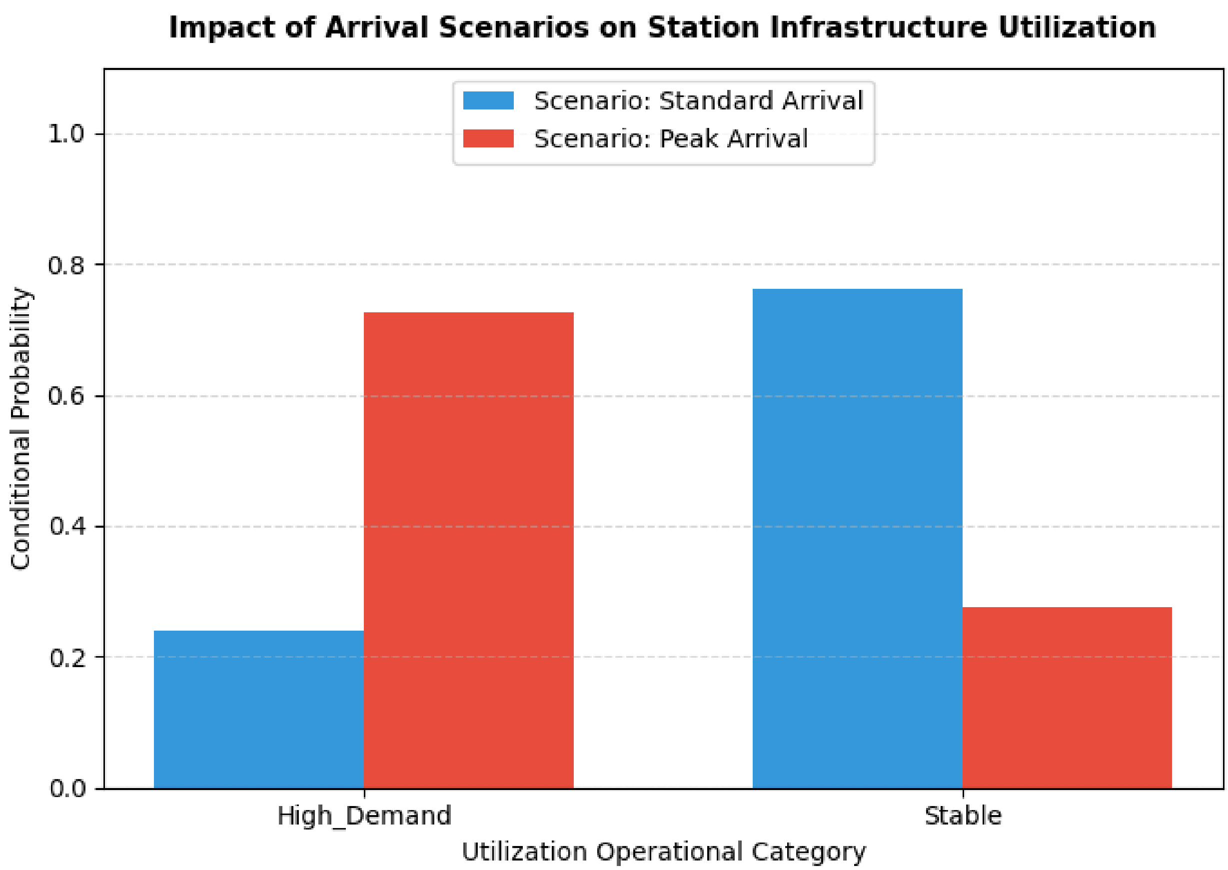


Figure (6): Proactive Scenario Analysis Tracing the Impact of Arrival Behaviors on Station Utilization Probability.

To position the proposed framework within the current state of the art, a comparative analysis of representative electric vehicle charging demand prediction models reported in the recent literature is presented in Table 4a.

Table (4a): Comparative Analysis of Representative EV Charging Demand Prediction Models.

Ref	Model	Climatic Factors	Evaluation Metric(s)	Reported Results
[14]	Deep Learning-based EV Load Forecasting	Yes	MAE, RMSE	Meteorological factors significantly improved short-term forecasting performance.
[28]	Deep Learning Model	No	Forecasting Metrics	Demonstrated superior short-term EV charging demand prediction capability.
[29]	Transformer-based Deep Learning	No	Forecasting Metrics	Outperformed several conventional forecasting models

				for EV charging demand prediction.
[30]	MCCNN-TCN	No	Forecasting Error Metrics	Improved forecasting performance over ANN, LSTM, CNN-LSTM, and TCN models.
[33]	Spatial-Temporal Graph Transformer Network	No	MAE and RMSE	Improved charging load forecasting through spatio-temporal feature extraction.
[40]	Hybrid Bayesian Network and Deep Learning	Yes	Reliability and Capacity Forecasting	Integrated climatic and reliability factors for EV charging capacity forecasting.
Proposed Work	Optimized Deep MLP (128-64-32)	Yes	Accuracy, Precision, Recall, and F1-score	Achieved 91.68% classification accuracy using socio-climatic features under extreme arid climatic conditions.

As depicted in Table 4, it can be observed that recent studies focus mainly on the forecast of EV charging demand by using deep learning techniques, transformer-based models, and graph neural networks. Even though there are several models that consider the time and space aspects of charging behavior, few of them take climate factors into account during their prediction process. In contrast, our proposed model considers socio-climate features, and we use an optimized DMLP model to classify charging demand conditions in extreme arid regions. Because of the differences in data sets and experimental settings in the literature, this comparison is made to place our model in context.

In order to complement the qualitative integration of findings from the domain (Table 4a) through the performance of direct quantitative benchmarking on the same set of tests under the same experimental conditions (N = 2,057), the baseline approaches of both time-series and deep sequence modeling techniques were compared to the proposed approach. According to Table 4b, although baseline recurrent neural networks such as LSTM had acceptable accuracy (82.15%), they also had convergence latency due to complicated temporal relationships. It is noteworthy that the proposed framework outperformed these baselines by achieving 91.68% of accuracy in less computational time (total convergence time was 142 s).

Table (4b): Quantitative Empirical Benchmarking Against Baseline Architectures.

Model Architecture	Primary Input Features	Test Accuracy (%)	Processing / Training Load
Classical SARIMA Baseline	Historical Demand Series	68.40% ± 2.10	Minimal (< 15s)
Standard LSTM Network	Multi-variate Sequences	82.15% ±1.45	High (510s)

MCCNN-TCN Architecture	Spatial-Temporal Streams	88.30 ± 1.10%	Very High (890s)
Proposed Optimized Framework	Socio-Climatic Features (Ψ)	91.68%	Optimized (142s total)

5. Conclusion and Future Work

This paper achieves in successfully developing and validating an adaptive socio-climatic deep learning architecture that will predict the use of the EV charging station during highly challenging climatic conditions. This is achieved through the combination of 20,569 simulated EV infrastructure utilization records with the NASA POWER meteorological dataset using a unified temporal key. From the experiment, it is evident that the transition from a non-optimal neural structure to a better structure, which is the three-layered deep Multi-Layer Perceptron (with a topology of 128-64-32), solved the problem of poor convergence. Hyper parameter optimization in this case led to the dramatic improvement of global classification accuracy by increasing it from an initial 56.8% to 91.68%. Another thing worth noting is that the implementation of a dropout value of 20% along with early stopping helped avoid overfitting. Cell-level validation carried out via the confusion matrix and conditional probability simulation revealed that the developed quantile split at the 55th percentile works accurately in separating operations into two distinct categories (Stable and High Demand). Thus, the obtained validation results prove that the developed model is a very efficient tool for avoiding grid congestion in areas where the climate conditions are harsh. The practical application of the predictive model involves using it for dynamic load balancing and thermal throttling when there are peak summer surges. Future research will consider expanding the socio-climate model to include IoT battery degradation information and assessing transfer learning among neighboring hyper-arid areas. Future work will be carried out along two distinct tracks. First, extending the model by incorporating spatial temporal graph neural networks to account for localized differences in grid routing patterns within the network. Secondly, deploying lighter versions of the optimized model within edge intelligence units present within the charging stations in order to estimate demand in a distributed fashion. Future work will investigate data-driven calibration and sensitivity analysis of the Hydro-Thermal Stress Index coefficients using real operational EV charging datasets collected from arid and hyper-arid regions.

Conflict of Interest: The authors declare that there are no conflicts of interest associated with this paper project. We have no financial or personal relationships that could potentially bias our work or influence the interpretation of the results.

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