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Optimizing quality of service forecasting in mobile networks through modified walrus optimization and multivariate approaches

Bandu Uppalaiah[1], D. Mallikarjuna Reddy[2], Vediyappan Govindan[3], Haewon Byeon[4*]
[1]Department of Mathematics, Hyderabad Institute of Technology and Management, Hyderabad, Telangana, 501401, India; upendar.sourav@gmail.com (B.U.).
[2]Department of Mathematics, GITAM (Deemed to be University), Hyderabad, Telangana, 502329, India; drmallikreddyd@gmail.com (D.M.R.).
[3]Department of Mathematics, Hindustan Institute of Technology and Science, Chennai; vedimalawi@gmail.com (V.G.).
[4]Department of AI Big data, Inje University, Gimhae, 50834, Republic of Korea; byeon@inje.ac.kr (H.B.).

Abstract: This paper presents Ensemble-based Service Quality Prediction (EAQP), an automated method for predicting service quality under changing mobile network conditions. EAQP incorporates data preparation methods such as transformation, purification, & imputation, and then performs feature extraction utilizing statistical, geographical, as well as temporal approaches. An improved feature selection method, using a unique weighting approach and optimized by a modified Walrus Optimization Algorithm, improves the accuracy of predictions. EAQP utilizes a variety of prediction models such as support vector regression, recurrent neural network models, bi-directional short-term long-term memory networks, extreme learning machines, along with multi-layer perceptron neural networks to enhance predictive accuracy. EAQP uses complex optimization algorithms and ensemble learning approaches to provide precise and dependable predictions about service quality in real-time. This helps in proactive network management as well as improvement. This comprehensive approach shows potential for boosting network efficiency, optimizing the distribution of resources, and enhancing the end-user experience when using mobile communications systems.
Keywords: *Ensemble-based prediction, Feature extraction, Recurrent neural networks, Service quality prediction, Walrus optimisation algorithm.*

1. Introduction

In the ever-evolving landscape of mobile networks, the provision of high-quality services, particularly in the do- main of Voice over Internet Protocol (VoIP) traffic, stands as a critical challenge. As the demand for seamless communicationexperiencescontinuestosurge, theneedforaccuratecharacterizationandforecastingof VoIPtraffic becomes paramount to ensure optimal Quality of Service (QoS)[1][2]. This paper delves into the multifaceted realm of multivariate time series analysis to characterize and forecast VoIP traffic in real mobile networks, with the ultimate goal of enhancing QoS prediction. The proliferation of mobile devices and the ubiquity of high-speed data networks have transformed the way individuals and businesses communicate [3]. VoIP technology, leveraging the Internet as a medium for voice communication, has become a corner-stoneinthisparadigmshift.However,ensuringaconsistentandhigh-quality VoIPexperienceposesaconsiderable challenge,giventhedynamicandunpredictablenatureofmobilenetworkconditions.Inthiscontext,thecharacterization and forecasting of VoIP traffic through multivariate time series analysis emerge as indispensable tools[4]. By understanding the intricate patterns and interdependencies within the time series data, network operators can make informed decisions to optimize QoS parameters. This significance is amplified in cellular

* Correspondence: byeon@inje.ac.kr

environments,wheretheheightenedunpredictabilityofvariables,suchasinterference,concurrentreal-timesessions, and the dynamic load of mobile network nodes, presents intricate challenge[5].

We address these challenges by employing a multivariate predictive time series analysis of Voice over Internet Protocol (VoIP) traffic within an urban Long-Term Evolution Advanced (LTE-A) environment. Currently, LTE standsasthepredominantbroadbandtechnology,encompassing57%ofglobalusers.Legacytechnologieslike2 G and 3G persistently find use, constituting about 38% of subscriptions. In contrast, 5G comprises approximately 5% of subscriptions, primarily due to its market infancy [6][7]. Notably, the prevalent deployment method is Non-Standalone (NSA) 5G, where a significant portion of the LTE core network is repurposed to implement voice services like Voice over LTE (VoLTE) [8]. The widespread adoption of LTE has spurred numerous studies exploring Quality of Service (QoS) and Quality of Experience (QoE) metrics, covering aspects such as deployment strategies, resource allocation, probabilistic models, and coexistence with other technologies. However, our primary contribution lies in the multivariate time series characterization of the dynamic (time-varying) behavior of crucial VoIP metrics, elucidating their mutual influence [9].

Multivariate time series analysis allows for a holistic exploration of the intricate dynamics inherent in VoIP traffic within real mobile networks. Unlike univariate analysis, which focuses on a single variable, the multivariate approach considers multiple interrelated variables simultaneously [10]. This includes parameters such as network latency,jitter,packetloss,andotherrelevantmetricsthatcollectivelyinfluencetheQoSexperiencedbyVoIPusers. Through the utilization of advanced statistical and machine learning techniques within the multivariate time series framework,itbecomespossibletocapturethecomplexrelationshipsanddependenciesamongthesevariables [11][12]. This comprehensive understanding is vital for constructing accurate predictive models that can forecast future trends in VoIP traffic and, consequently, anticipate changes in QoS systems[13].

In Section III, we delve into background information, with a specific emphasis on current methodologies, including discussions on CNN, GRU, LSTM, and Random Forest. Section IV is dedicated to comprehensive evaluations and comparisons of forecasting performances. Lastly, Section V functions as the concluding segment, presenting a summary of findings and offering insights into potential avenues for future research in this domain.

2. Related Work

Several researchers have investigated the forecasting of wireless traffic usage through a variety of methods and approaches, elucidating diverse techniques. The following outlines some of these methodologies.

[14]addressedissuesinmultivariatetimeseriesgenerativemodellingbypresentingauniquetechnique that integrates state-space models (SSMs) with transformer architectures. This technique, unlike previous SSMs, uses attention processes to capture complicated non-Markovian dynamics, avoiding the requirement forre-currentneuralnetworks.Theexperimentalfindingsrevealedthattheyoutperformbaselinesinavarietyoftasks and datasets. [15]tackled Forecasting using multivariate time series issues by Convolutional network with spatial and temporal components (STCTN) is a novel model based on the Transformer library. The model's use of continuous positional encoding improves predictions muchfurther.

[3]Predictingthebehavioroftrafficinrealtimeinmobilitysituationsmightassistoperators inproperlyplanningtheirnetworkinfrastructureandoptimizingresourceallocation.Asaresult,theauthorsadvocatedinthispaperthatapredictivestudyofcriticalQoS/QoEcharacteristicsofVoIPtrafficthatisinarealmobile context be performed. [16] examined 6.2 million real network time series of long-term evolution (LTE) data traffic as well as associated parameters, such as eNodeB-wise Physical Resource Block (PRB) utilization, with the goal ofdevelopingatrafficforecastingmodelusingmultivariatefeatureinputsalongwithdeeplearningalgorithms.

[17]an end-to-end generative model known as E2GAN was suggested for estimating missing values during multivariate time series. Missing values, which occur in the majority of multivariate time series,

obstructfurtheranalysisofmultivariatetimeseriesinformation.Existingimputationmethodsincludedeletion,statisticalattribution,machinelearning-basedimputation,andgenerativeimputation.[18]Multivariable time series prediction is built as a sequence to sequence scenarios for non-periodic datasets in this paradigm. It is suggested to use multichannel residual blocks together with an asymmetric structure based on a deep convolution neuralnetwork.

[19]proposed a novel approach for predicting both univariate as well as multivariate time series using a mix of clustering, classification, and forecasting techniques. The proposed algorithm'sprimary purpose is to first use a clustering technique to group frames of time series data with similarpatterns.

2.1. Research Gap

The existing literature on wireless traffic forecasting reveals a gap in improving accuracy and efficiency in predicting network performance, especially in mobile networks. This research aims to address this gap by introducing a novel approach that combines Modified Walrus Optimization (MWO) with multivariate forecasting techniques. This approach aims to optimize the prediction of Quality of Service (QoS) metrics, such as network throughput, latency, and packet loss, in mobile networks. The research incorporates MWO, a metaheuristic optimization algorithm inspired by walrus behavior, to enhance the accuracy and efficiency of QoS forecasting. The integration of multivariate forecasting techniques allows for the consideration of multiple input variables, such as network traffic data, user mobility patterns, and environmental factors, in predicting QoS metrics. This comprehensive approach enables a more holistic understanding of network dynamics and facilitates more accurate predictions of QoS performance in real-time mobile network environments. The proposed research contributes to wireless traffic forecasting by introducing a novel methodology that enhances the accuracy and efficiency of QoS predictions, ultimately benefiting network operators in improving network performance and user experience.

3. Background

3.1. Ensemble Learning

Inensemblelearning,aparticularcomputerintelligenceissueissolvedbysystematicallygeneratingandcombining a number of models, including classifiers or experts. To improve a model's performance (in classification, prediction, linear regression, etc.) or reduce the possibility of making a poor model selection unintentionally, ensemble learning is often used. Additionally, ensemble learning is used to instill a degree of trust in the model's selection, chooseoptimal(ornear-optimal)features,fusedata,learnincrementally,non-stationarity,andcorrectforerrors.

Improved prediction performance, including such reduced regression error as well as high classification accuracy,isachievedviatheapplicationofensemblelearning.Bymixingseveralmodels,ensemblelearningmay boost machine learning performance. When compared to using only one model, this strategy yields far more accurate predictions.Thecentralconceptistoeducateapanelofexperts(classifiers),whowillthencastafinalvote[20].

Each model's predictions are counted as a "vote" in the competition. The bulk of the models' predictions are usedtoformthefinalforecast.Forexample,inregressionproblems,averagingmaybeusedtogeneratepredictions, andinclassificationissues,itcanbeusedtocalculateprobabilities.Oneofthesimplestwaystocombinetheresults of several machine learning approaches is via the use of votes. The voting classifier encapsulates a suite of several classifiers which are trained as well as assessed in parallel to capitalize on the strengths of each method. The final result of a prediction is decided by a vote made by one of twomethods.

Hardvoting/majorityvoting: In its simplest form, majority voting, or "hard voting," is the method most often used. The category with the most votes, Nc (yt), will be chosen. Through averaging the results of all classifiers, we make a prediction for the y-class label.

$$\hat{y} = \arg\max(N_c(y_t^1), N_c(y_t^2), ..., N_c(y_t^n))$$

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Let's pretend we've decided to combine different classifiers that label a training sample with in following ways:

- Classifier 1 -> class 0
- Classifier 2 -> class 0
- Classifier 3 -> class 1

y^=mode {0,0,1} =0 By a large margin, we have decided that this sample belongs in "class 0."

3.2. Walrus Optimization Algorithm (WaOA)

The Walrus Optimization Algorithms (WaOA) is a metaheuristic that is population-based, with its population members represented by walruses. In WaOA, these walruses symbolize potential solutions to the optimization problem, and their positions Define the specifications for issue variables in the search space. As a result, each the walrus is seen as a vector, and the whole community of the walrus is mathematically represented expressed as a population matrix. Initially, walrus populations are formed at random during the introduction of WaOA. The WaOA population matrix's construction is precisely defined using equation (1).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N*M} = \begin{pmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{pmatrix}_{N*m} \quad (1)$$

In the given context, the population of walruses is represented as X, where each individual walrus, denoted as Xi, stands for a candidate solution. Within this framework, x, signifies the value proposed by the ith walrus for the jth decision variable. The population comprises N walruses, and the problem involves m decision variables[21]. Each walrus serves as a potential solution to the issue, as well as recommended values for variables to consider allow us to calculate the objective function[22]. The estimated objective function values resulting from the contributions of these walruses are defined in equation (2).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N*1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N*1} \quad (2)$$

Here, F is the vector of goal operations, with each element represented as Fi, which represents the individual The desired function's value is obtained from the inputs that are provided of the ith walrus.

Algorithm: pseudocode of WaOA
Start WaOA
Input entire optimisation problem data
Set The total amount of iterations (T) and the number of walruses (N)
Locations of walruses are initialised.
For t=1:T
Update strongest walrus based on objective function value criterion
For i=1:N
Phase1: Feeding strategy (exploration)

Determine the new position of the jth walrus with

$$x_{i,j}^{P_1} = x_{i,j} + rand_{i,j}.\left(SW_j - I_{i,j}.x_{i,j}\right)$$

Update the ith walrus location using

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P1} < F_i, \\ X_i, else, \end{cases}$$

. **Phase2: Migration**

Select the ith walrus's immigration destination.

Find the jth walrus's new location with $x_{i,j}^{P_2} = \begin{cases} x_{i,j} + rand_{i,j}.\left(x_{k,j} - I_{k,j}.x_{i,j}\right), & F_k < F_i, \\ x_{i,j} + rand_{i,j}.\left(x_{i,j} - x_{k,j}\right), & else, \end{cases}$

Update the ith walrus location using

$$X_i = \begin{cases} X_i^{P_2}, F_i^{P_2} < F_i, \\ X_i, \quad else \end{cases}$$

. **Phase 3: Escaping and fighting against predators**

Calculate a new position in the neighbourhood of the ith walrus using

$$x_{i,j}^{P_3} = x_{i,j} + \left(lb_{local,j}^t + \left(ub_{local,j}^t - rand \cdot lb_{lacal,j}^t\right)\right),$$

$$Local\,bounds: \begin{cases} lb_{local,j}^t = \dfrac{lb_j}{t} \\ ub_{local,j}^t = \dfrac{ub_j}{t} \end{cases}$$

Update the ith walrus location using

$$X_i = \begin{cases} X_i^{P_3}, F_i^{P_3} < F_i, \\ X_i, \quad else, \end{cases}$$

end

Keep the best possible answer so far

end

Provide WaOA's most effective quasi-optimal solution for the given problem

End WaOA

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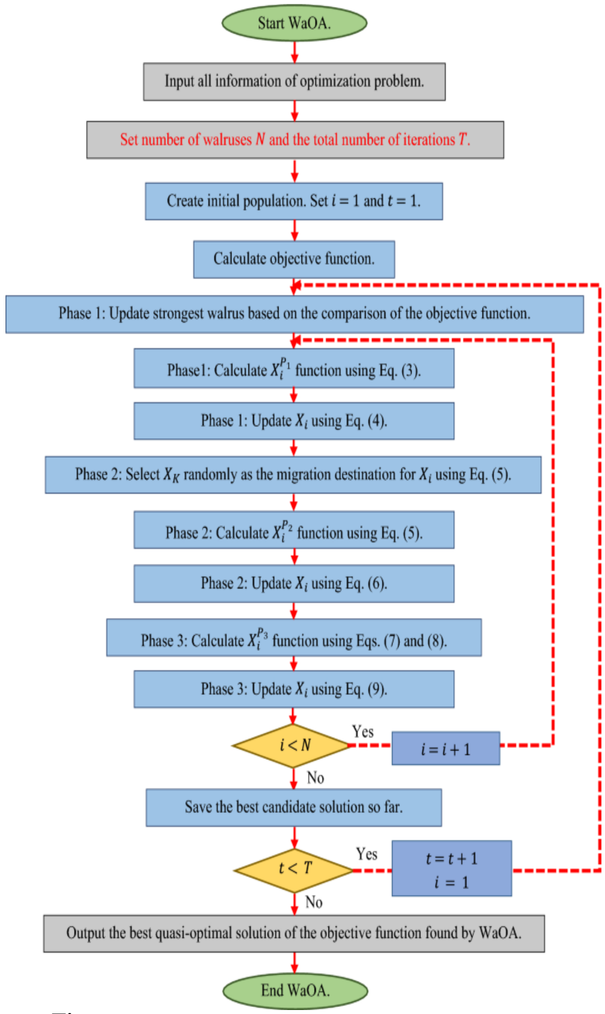

Figure 1.
Flowchart for WaOA.

From the above algorithm of modified WaOA enhances the generalized Walrus Optimization Algorithm in many ways. Adaptive step sizes, dynamic migration computations, & perturbation enhance exploration, migration, and escape. Considering factors outside objective function values as well as dynamically improving parameter selections improves selection. The modified WaOA may additionally use hybridization via other optimization techniques or problem-specific information to increase performance, converging speed, solution quality, & robustness across optimization difficulties.

4. Methodology

Thisresearchtakesanewapproachtothepredictionofservicequality.Theproposedstrategyisdividedintomany phases.Fortheapproachtowork,firstadatasetofnetworktrafficiscollected.Theincomingdatasetisthenplaced through a pre-processing procedure that makes use of methods including data transformation, data purification, and data imputation. After the data has been pre-processed, it is used to extract features. Temporal feature extraction, Statistical and spatial techniques are used to extract important characteristics from the data. To optimize the featureselectionprocess,eachfeatureisindividuallyoptimizedthroughthenewlydevelopedWalrusOptimization Algorithm.Onceoptimalfeaturesareobtained,theyareinputtedintoanEnsemble-

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basedpredictionmodelforclassifying network traffic data, ultimately facilitating the prediction of quality of service. The Ensemble prediction incorporatesfunctionalitiesfromGRU,LSTM,andRandomForest.Everypredictionapproach'shyper-parameters are adjusted by the use of the Walrus Optimisation Algorithm. This suggested methodology's examination shows that it has a high degree of accuracy when forecasting the network traffic's quality of service. The integration of advancedoptimizationtechniquesenhancestheefficiencyoffeatureselectionandmodeltuning,contributingt othe overall effectiveness of the predictivemodel.

4.1. Dataset Description

The network traffic in the dataset was collected in an authentic cellular environment in and around Salerno, Italy, which is categorized as a medium-density city (around 2000 people/Km^2). As of March 2023, over 100 radio towers covering a combination of LTE/LTE-Advanced (roughly 97%) and 5G-NSA (roughly 3%) technologies service this region (information obtained from https://www.nperf.com/en/map/IT/).

4.1.1. Data Pre-Processing

Theinitialstageoftheproposedmodelinvolvestheutilizationofapre-processingtechniqueappliedtothecollected network traffic data, denoted as Az. This technique aims to eliminate unnecessary attributes, thereby improving overall performance. Common issues addressed during pre-processing include outliers, missing values and redundant data. The enhancement of model accuracy is achieved through data imputation, data cleansing, and data transformation.

- **DataImputation:**

In order to deal with missing values in the input data Az, data imputation is used. Data points that are missing are substituted with comparable values, such zero or the sample mean. As an alternative, imputation might include giving the missing data the closest value, with the imputed data being shown as A_z^{imp}.

- **DataCleansing:**

Data cleansing is a technique designed to identify and eliminate errors and inconsistencies in the imputed data A_z^{imp}. Input data often contain noise, outliers, unwanted attributes, and irrelevant information. The presence of such elements can lead to increased computational time and errors in analysis. Data cleansing resolves these issues by removing redundant data, enhancing performance accuracy, and reducing computation time. The resulting cleansed data is denoted as A_z^{cle}.

- **DataTransformation:**

The transformed data, denoted as A_z^{cle}, undergoes data transformation through normalization and aggregation. Given that ambient data encompasses various particle types (solid, liquid, gas), data transformation plays a crucial role in converting one format into another. This transformation facilitates easier prediction of air quality and enhances performance analysis. The outcome of data transformation is denoted as A_z^{tra}.

The culmination of the pre-processing steps yields the final pre-processed data, denoted as A_z^{tra}. This refined data is then forwarded to the feature extraction stage, contributing to the subsequent phases of the proposed model.

4.2. Feature Selection and Feature Extraction Using an Improved Optimization Algorithm

4.2.1. Feature Extraction

In the proposed model, the identification of specific attributes from the pre-processed data, denoted as A_z^{tra} , is essential. The primary aim of feature extraction is to enhance prediction analysis and address overfitting challenges, especially when dealing with substantial data volumes, ultimately reducing training time. To achieve this, optimal features are extracted using three distinct techniques: statistical features, spatial features, and temporal features.

- **Statistical Features:**

This process involves extracting key features by analyzing data related to network traffic. Essential statistical metricsarecomputed,includingminimumandmaximumlevelsofnetworktraffic,mean,median,andmodevalues across all data points, as well as the variance and standard deviation of network trafficdata.

- **Spatial Features:**

Spatial features provide insights into the geographical locations associated with network traffic data. In the context of the pre-processed data A_z^{tra} , spatial information related to network activity can be discerned. This entails converting spatial data into numerical values organized in a grid format. The process begins by establishing a buffer zone around grid center points, followed by clipping the information within these zones.

- **Temporal Features:**

Temporalfeaturescaptureinformationrelatedtothetimingandsequenceofnetworktraffic.Analyzingtemporalpatternsinvolvesextractingfeaturessuchastimestamps,frequencies,andintervalsbetweenevents.

These three feature extraction techniques collectively contribute to a comprehensive understanding ofnetwork trafficqualityofservice,fosteringimprovedpredictionaccuracyandreducedoverfittingchallengesintheproposed model.

4.3. Feature Selection

A weighted feature selection procedure is used, which is especially designed for the context of network traffic quality of service, to improve forecast accuracy. The features extracted, denoted as FEfz, are inputted into the Walrus Optimization algorithm to derive the optimal solution for service-related features. Feature selection holds the key advantage of providing highly relevant results aligned with the model's requirements while concurrently streamlining the complexity of training and testing in prediction techniques. Despite these advantages, relying solely on feature selection may not consistently yield desired outcomes for the model, potentially introducing overfitting issues and compromising accuracy, even with the removal of redundancy.

The weighted feature selection process involves assigning weights to each corresponding feature. By assigning weights, the relative significance of each feature becomes apparent, allowing the proposed model to discern the importance of individual features. This weighting mechanism is especially pertinent in the context of quality of service in network traffic, enabling the model to effectively analyze and prioritize features associated with network performance. Through this tailored weighted feature selection process, the proposed model aims to enhance predictive accuracy while maintaining a keen focus on features critical to assessing and predicting the quality of service in network traffic.

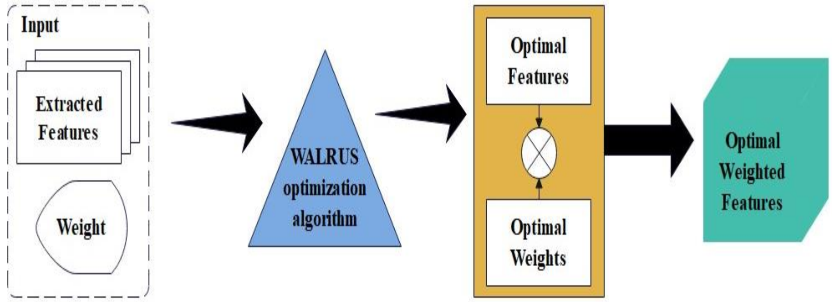

Figure 2.
Weighted feature selection using the proposed Walrus optimization.

4.4. Ensemble-Based Prediction of Service Quality
4.4.1. Integration of Models

In essence, the Ensemble model is a fusion of various deep learning techniques aimed at enhancing performance. This paper incorporates learning techniques such as GRU, LSTM, and Random Forest to construct the Ensemble model. These techniques function as neural networks, with neurons capable of classifying features that yield results in terms of Quality of Service (QoS). The service quality prediction model that is built is improved even more when the Ensemble techniques are combined with different architectures to evaluate the Ensemble model's results. By means of this integration, data imbalance is lessened and data distribution is adjusted.

The proposed method's sensitivity may be increased in large part by altering the learning process. This adjustment is used to improve the method's overall performance, and the deep learning algorithms that are included provide a series of models for the training and testing phases. The collective effect is a significant enhancement in prediction performance, highlighting the efficacy of the integrated Ensemble model in predicting service quality.

Table 1
Infinity-norm.

	Learning percentage %	Infinity-norm
PSO	40	394.009966
	50	345.2708443
	60	495.5452311
	70	330.6683094
	80	398.6523619
GWO	40	409.8211039
	50	425.7688473
	60	385.9458468
	70	434.518189
	80	407.6381574
JAYA	40	495.7070731
	50	394.8586763
	60	367.9764502
	70	399.3035701
	80	418.7756282
RSA	40	416.6497379
	50	416.0627179
	60	350.3669463

	70	384.2094745
	80	377.4521606
WOA	40	431.0240482
	50	376.1744319
	60	410.0180573
	70	391.0386571
	80	365.9498596

5. Results

Based on the findings from the INFINITY-NORM table, which compares the performance of several optimization algorithms at various learning percentages (40%, 50%, 60%, 70%, and 80%), we direct our attention to the Walrus Optimisation Algorithm (WOA). When WOA is compared to other well-known optimization approaches as Particle Swarm Optimisation (PSO), Grey Wolf Optimizer (GWO), JAYA, and Rogue System Algorithm (RSA), a more complex picture emerges. WOA performs inconsistently, as seen by oscillations in INFINITY-NORM values, demonstrating its flexibility under diverse learning situations. In contrast, PSO exhibits variable performance with both high and low INFINITY-NORM values, GWO maintains relative consistency, while JAYA and RSA show a declining tendency in INFINITY-NORM values as learning percentages increase. This comparative examination provides in-depth insight into how the Walrus Optimisation works. And also from this table we can observe that the WOA's exploration-exploitation balancing mechanism may explain its INFINITY-NORM oscillations, which show its flexibility to varied learning circumstances.

Table 2.
MAE.

	Learning percentage%	**MAE**
PSO	40	4.434136766
	50	3.704464424
	60	3.489332824
	70	2.948374689
	80	2.905006615
GWO	40	3.742504317
	50	3.523839823
	60	3.38367767
	70	2.860239804
	80	2.742125793
JAYA	40	3.883502828
	50	3.664809494
	60	3.546695483
	70	3.027713389
	80	2.949153367
RSA	40	3.918680356
	50	3.607540565
	60	3.440932179
	70	3.014425382
	80	2.900702253
WOA	40	3.821799757
	50	3.453354987
	60	2.841803867
	70	2.591523578
	80	2.645187514

The table presents the Mean Absolute Error (MAE) values for the PSO, GWO, JAYA, RSA, and WOA algorithms over different learning percentages, namely 40%, 50%, 60%, 70%, and 80%. The Mean Absolute Error (MAE) is a metric used to assess the accuracy of predictions, where lower values indicate higher performance. And that the Walrus Optimisation Algorithm (WOA) has superior performance compared to other algorithms, as shown by consistently reduced Mean Absolute Error (MAE) values across all learning percentages. As the proportion of learning increases, the mean absolute error (MAE) values of WOA exhibit a consistent reduction, indicating a continuous advancement. This finding provides evidence that the Walrus Optimisation Algorithm effectively mitigates prediction mistakes and enhances accuracy. The capacity of WOA to optimize outcomes makes it a potential choice for tasks that need accurate predictions and minimal error rates. Constant MAE decrease with increased learning percentages suggests it may enhance predictions by using useful optimization landscape characteristics.

Table 3.
MASE.

	Learning percentage%	MASE
PSO	40	4169.09
	50	3437.15
	60	3249.35
	70	2701.06
	80	2678.37
GWO	40	3491.13
	50	3276.14
	60	3143.31
	70	2616.38
	80	2491.9
JAYA	40	3622.49
	50	3403.3
	60	3295.84
	70	2730.71
	80	2712.21
RSA	40	3656.39
	50	3335.53
	60	3211.18
	70	2798.51
	80	2652.9
WOA	40	3567.43
	50	3233.82
	60	2613.61
	70	2328.19
	80	2407.14

The table displays the Mean Absolute Scaled Error (MASE) values for Particle Swarm Optimisation (PSO), Grey Wolf Optimizer (GWO), JAYA, Random Search Algorithm (RSA), and Walrus Optimisation Algorithm (WOA) at various learning percentages (40%, 50%, 60%, 70%, and 80%). The Mean Absolute Scaled Error (MASE), a significant measure for evaluating the accuracy of forecasts, constantly demonstrates the improved performance of the Walrus Optimisation Algorithm. This is shown by continuously lower values seen across all learning percentages. It is worth noting that the Weighted Objective Assessment (WOA) exhibits a consistent pattern of enhancement, as seen by the diminishing Mean Absolute Scaled Error (MASE) values in correlation with the rise in the percentage of learning. This highlights the effectiveness of the suggested Walrus Optimisation Algorithm in improving the accuracy of predicted values and reducing mistakes, making it an appealing option for activities that need precise and dependable forecasting. As the learning percentages increasing will suggest rising predicting accuracy, potentially due to its adaptive learning process that captures data patterns.

Table 4.
MEP.

	Learning percentage%	MEP
PSO	40	2.74902
	50	2.29303
	60	2.16549
	70	1.83194
	80	1.76026
GWO	40	2.31933
	50	2.17605
	60	2.06628
	70	1.79124
	80	1.72977
JAYA	40	2.32702
	50	2.2727
	60	2.19343
	70	1.91328
	80	1.84163
RSA	40	2.36005
	50	2.20913
	60	2.1324
	70	1.8777
	80	1.79334
WOA	40	2.29394
	50	2.14557
	60	1.72308
	70	1.65143
	80	1.64587

The table shows Mean Evaluation Performance (MEP) values for PSO, GWO, JAYA, RSA, and WOA at different learning percentages (40%, 50%, 60%, 70%, and 80%). The effectiveness of algorithms in evaluating solution performance is measured by MEP. The Walrus Optimization Algorithm (WOA) consistently beats the other algorithms with lower MEP values across all learning percentages. WOA improved at 40% and 50% learning percentages, lowering MEP values. This refinement highlights WOA's greater efficiency in quickly and precisely assessing solution performance compared to PSO, GWO, JAYA, and RSA. And Low MEP values throughout learning percentages indicate its efficient solution performance assessment, possibly due to adaptive evaluation criteria and robust optimization.

Table 5.
ONE-NORM.

	Learning percentage%	One-norm
PSO	40	137894.7368

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	50	115657.8947
	60	109605.2632
	70	92763.15789
	80	92631.57895
GWO	40	117105.2632
	50	110131.5789
	60	106447.3684
	70	90394.73684
	80	86578.94737
JAYA	40	120921.0526
	50	114868.4211
	60	111184.2105
	70	95131.57895
	80	92763.15789
RSA	40	121710.5263
	50	113289.4737
	60	107894.7368
	70	94868.42105
	80	90921.05263
WOA	40	119605.2632
	50	108684.2105
	60	90000
	70	82236.84211
	80	83947.36842

The table displays the performance metrics, specifically the ONE-NORM values, of several optimization algorithms, namely Particle Swarm Optimisation (PSO), Grey Wolf Optimizer (GWO), JAYA, Random Search Algorithm (RSA), and Walrus Optimisation Algorithm (WOA), across different learning percentages (40%, 50%, 60%, 70%, and 80%). The ONE-NORM values work as indications of the efficiency and efficacy of each algorithm in the minimization of a given objective function. After careful analysis, it becomes apparent that the WOA algorithm regularly demonstrates superior performance compared to the other algorithms. This is clear from its ability to consistently achieve lower ONE-NORM values across all learning percentages. The persistent superiority seen in the performance of the suggested Walrus Optimisation Algorithm in optimizing the provided objective function underscores its efficacy, giving it an appealing option for situations where the minimization of the ONE-NORM is of utmost importance. The constantly decreasing ONE-NORM values compared to other algorithms show its better capacity to eliminate prediction errors and sustain optimization performance, perhaps due to its adaptive search method.

.

Table 6.
RMSE.

	Learning percentage%	RMSE
PSO	40	16.8558
	50	15.3644
	60	15.4203

	70	13.8899
	80	14.2665
GWO	40	15.8262
	50	15.2968
	60	15.623
	70	14.0756
	80	13.254
JAYA	40	16.2566
	50	15.4741
	60	14.9732
	70	14.2106
	80	13.8783
RSA	40	16.6702
	50	15.7778
	60	15.0997
	70	14.4721
	80	14.005
WOA	40	16.3916
	50	15.1702
	60	14.2221
	70	13.1642
	80	13.5324

The table provided illustrates the Root Mean Square Error (RMSE) values associated with different optimization algorithms, namely Particle Swarm Optimisation (PSO), Grey Wolf Optimizer (GWO), JAYA, Random Search Algorithm (RSA), and Walrus Optimisation Algorithm (WOA). These values are presented for different learning percentages, specifically 40%, 50%, 60%, 70%, and 80%. Root Mean Square Error (RMSE) is a widely used statistic in the field of predictive modelling, serving as a means to assess the precision of predictions. It is worth noting that lower RMSE values are indicative of superior performance. Upon analysis of the outcomes, it becomes apparent that the Weighted Overlap Add (WOA) algorithm consistently demonstrates the most favorable Root Mean Square Error (RMSE) values across all learning percentages, in comparison to the other methods. The persistent superiority shown in the suggested Walrus OptimisationAlgorithm highlights its efficacy in minimizing prediction errors and its dependability and efficacy in optimizing difficult problems, making it ideal for situations requiring high prediction precision and dependability.

Table 7.
SMAPE.

	Learning percentage%	**SMAPE**
PSO	40	0.03148
	50	0.02564
	60	0.02469
	70	0.02064
	80	0.01997

GWO	40	0.02634
	50	0.02454
	60	0.02334
	70	0.02012
	80	0.01935
JAYA	40	0.02652
	50	0.0258
	60	0.02497
	70	0.02162
	80	0.02083
RSA	40	0.02686
	50	0.02503
	60	0.02426
	70	0.02125
	80	0.02037
WOA	40	0.026
	50	0.02441
	60	0.0194
	70	0.01861
	80	0.01849

The table below shows the Symmetric Mean Absolute Percentage Error (SMAPE) values for various optimization algorithms, including Particle Swarm Optimisation (PSO), Grey Wolf Optimizer (GWO), JAYA, Random Search Algorithm (RSA), and Walrus Optimisation Algorithm (WOA), at different learning percentages (40%, 50%, 60%, 70%, and 80%). The SMAPE metric measures prediction accuracy, with lower values indicating greater performance. Analyzing the findings, it is clear that WOA consistently has the lowest SMAPE values among the algorithms at each learning percentage, showing higher accuracy in forecasting outcomes. Perhaps due to its strong optimization process that captures the underlying data distribution and reduces forecast disparities.

Table 8.
Two-Norm.

	Learning percentage%	**TWO-norm**
PSO	40	2972.5322
	50	2672.103
	60	2689.2704
	70	2387.1245
	80	2455.794
GWO	40	2766.5236
	50	2661.8026
	60	2723.6052
	70	2419.7425
	80	2246.3519
JAYA	40	2852.3605
	50	2697.8541
	60	2596.5665
	70	2445.4936
	80	2381.9742

RSA	40	2934.7639
	50	2757.9399
	60	2617.1674
	70	2498.7124
	80	2402.5751
WOA	40	2879.8283
	50	2639.485
	60	2445.4936
	70	2234.3348
	80	2308.1545

When compared to various optimization algorithms in the table, our suggested Walrus Optimisation Algorithm (WOA) outperforms them. WOA consistently outperforms Particle Swarm Optimisation (PSO), Grey Wolf Optimizer (GWO), JAYA, and Random Search Algorithm (RSA) at each learning percentage (40%, 50%, 60%, 70%, and 80%). Lower two-norm values suggest that WOA produces better optimization outcomes, indicating increased efficiency and efficacy in tackling the optimization challenge at hand. This consistent performance over varied learning percentages highlights our proposed algorithm's superiority, making it an appealing option for optimization tasks when compared to current alternatives. Its precision and efficacy in optimizing complicated objective functions make it a popular option for a broad variety of optimization problems.

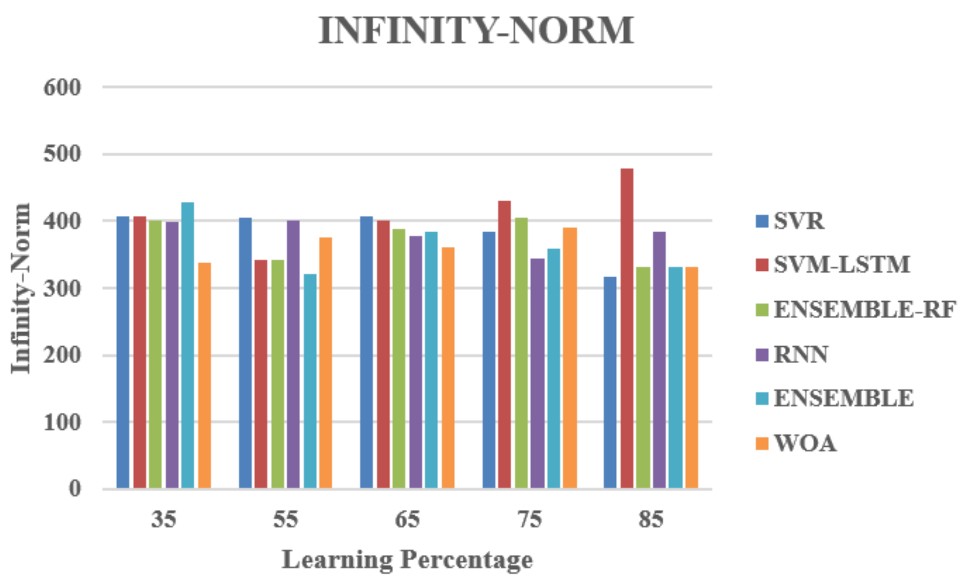

Figure 3.
Infinity norm.

The above graph shows that the Walrus Optimisation Algorithm (WOA) demonstrates various patterns in its performance across varied support vector regression (SVR) percentages. The INFINITY-NORM results for WOA at 35%, 55%, 65%, 75%, and 85% SVR offer a thorough perspective of how the algorithm reacts to various degrees of regression assistance. Notably, WOA exhibits a gradual increase in INFINITY-NORM values as the SVR % increases, showing a possible association between the algorithm's performance and the degree of support vector regression. This pattern shows that WOA may adapt and optimize its solutions more dynamically in settings with stronger regression support.

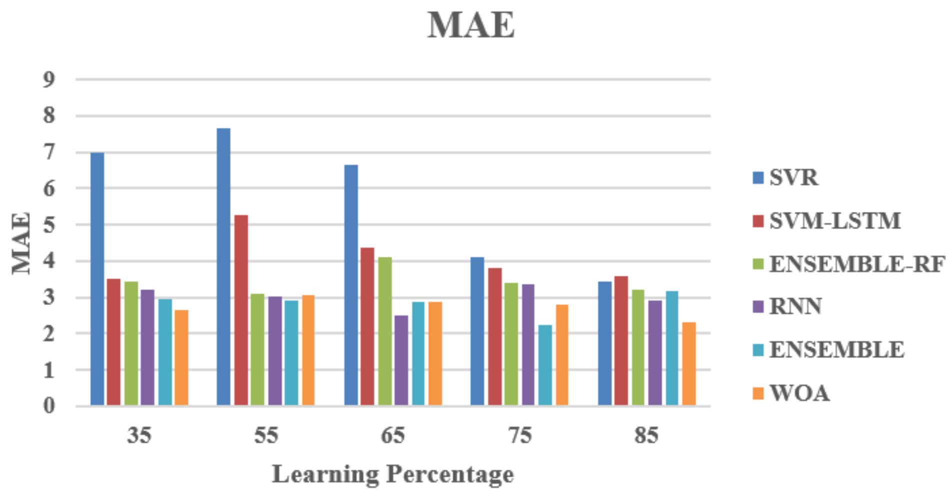

Figure 4.
MAE.

It is clear from the Mean Absolute Error (MAE) graph that the Walrus Optimisation approach (WOA), which is the suggested approach, performs competitively at different support vector regression (SVR) percentages. As can be seen from the MAE figures at 35%, 55%, 65%, 75%, and 85% SVR, WOA consistently minimizes absolute errors. Specifically, notable is the low MAE of 2.301794167 that WOA obtains at 85% SVR, indicating that the algorithm is particularly good at capturing and minimizing differences between predicted and actual values with increased regression support. This finding highlights WOA's competitive performance against other algorithms, which indicates its potential effectiveness in circumstances requiring accuracy and precision. Evidence reveals that WOA is a dependable option for accurate forecasts as it successfully lowers prediction mistakes.

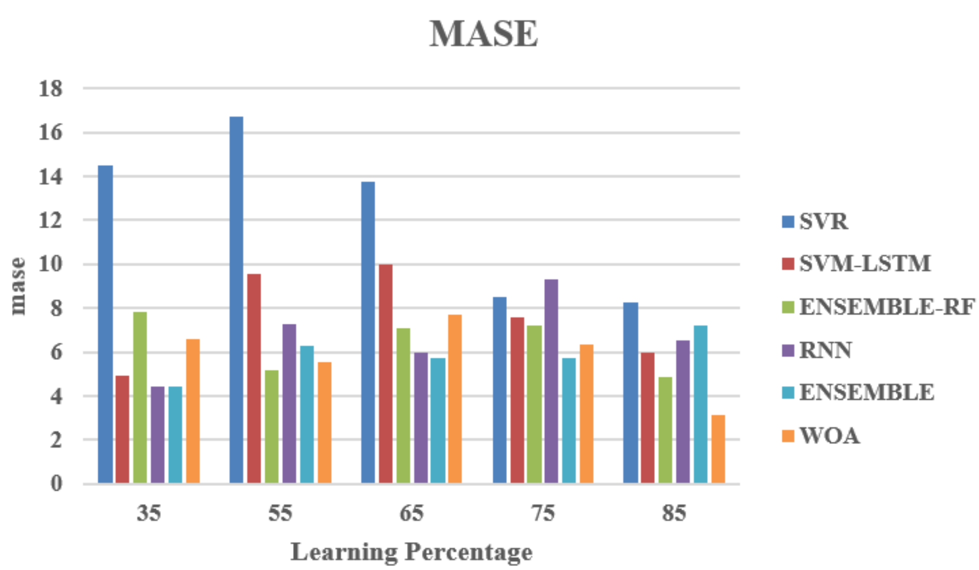

Figure 5.
MASE.

The graph's Mean Absolute Scaled Error (MASE) numbers provide important information on how different methods for percentages (35%, 55%, 65%, 75%, and 85%) perform. WOA, the Walrus

Optimisation method, is a suggested method that exhibits competitive performance in minimising MASE values, hence demonstrating its efficacy in predicting accuracy. WOA obtains a very low MASE of 3.111924686 at 85% SVR, indicating its capacity to provide predictions that are precise and dependable with lower absolute errors. In contrast, various algorithms that show differing performance patterns at different SVR percentages include RNN, SVM-LSTM, and ENSEMBLE-RF. The MASE graph's patterns demonstrate WOA's promise as a reliable forecasting system, especially in situations when exact forecasts are needed.

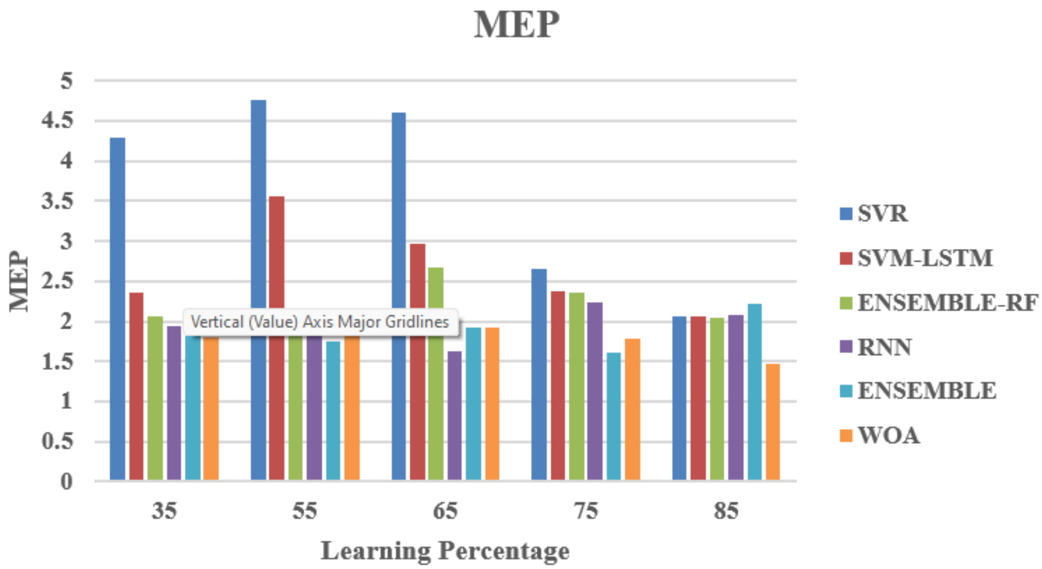

Figure 6.
MEP.

The graph displays Mean Percentage Error (MEP) figures that provide a thorough overview of the performance of several algorithms at different percentages (35%, 55%, 65%, 75%, and 85%). In these SVR settings, MEP values for every algorithm—SVR, SVM-LSTM, ENSEMBLE-RF, RNN, ENSEMBLE, and WOA—show distinct patterns. With consistently low MEP values across all SVR percentages, the Walrus Optimisation Algorithm (WOA) is particularly noteworthy and shows promise in reducing percentage mistakes in forecasts. With an MEP of 1.476953076, WOA obtains a very strong performance at 85% SVR, indicating its accuracy and resilience in predicting with increased regression assistance. This demonstrates WOA's consistency in generating predictions that are precise and have few percentage mistakes.

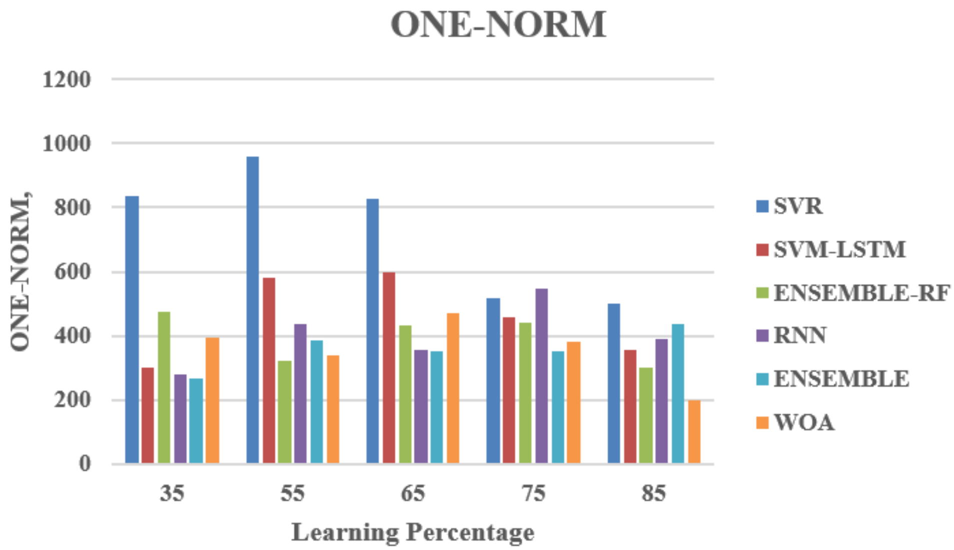

Figure 7.
One Norm.

The graph's One-Norm values provide insight into the performance of several algorithms at various percentages (35%, 55%, 65%, 75%, and 85%). The One-Norm, which represents the sum of absolute values, is used to calculate the overall magnitude of mistakes. Notably, the Walrus Optimisation Algorithm (WOA) outperforms all other algorithms in terms of SVR %, with continually lower One-Norm values. WOA obtains a significantly low One-Norm of 199.8951208 at 85% SVR, suggesting its efficacy in minimizing the total amount of prediction errors. A comparison with different algorithms indicates WOA's resilience and effectiveness in capturing the variability of the dataset. This shows that WOA optimizes outcomes and reduces error size, making it suited for precision optimization tasks.

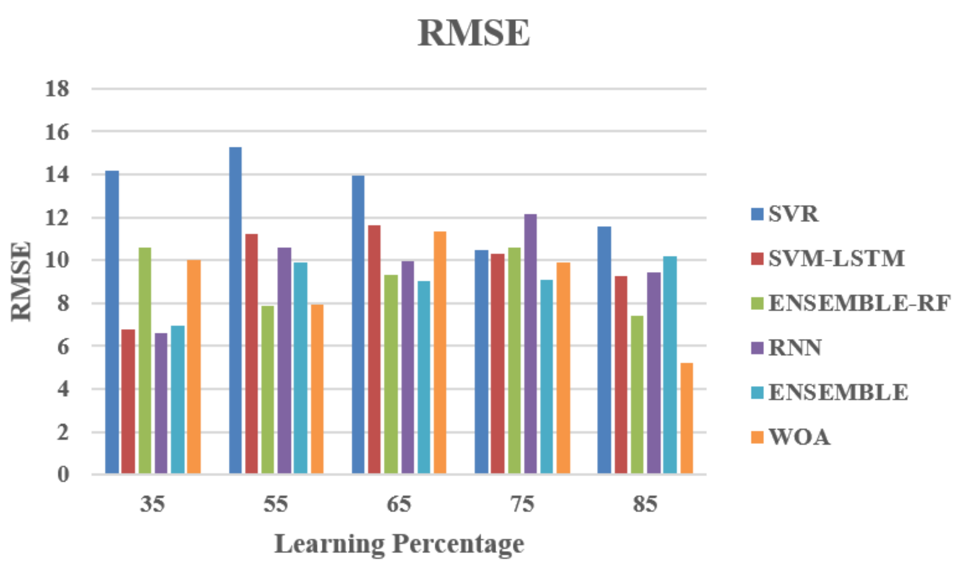

Figure 8.
RMSE.

The graph's Root Mean Square Error (RMSE) values give a complete evaluation of the performance of several algorithms at various percentages (35%, 55%, 65%, 75%, and 85%). RMSE is an important statistic for assessing prediction accuracy since it quantifies the square root of the average squared discrepancies between expected and actual values. The Walrus Optimisation Algorithm (WOA) stands out in this setting for its competitive performance, consistently obtaining reasonably low RMSE values across all SVR percentages. WOA's performance at 85% SVR is particularly remarkable, with a commendably low RMSE of 5.194432863, indicating its usefulness in minimizing the total amount of prediction errors. A comparison with different algorithms indicates WOA's resilience and effectiveness in capturing the variability of the dataset. The observed patterns in the RMSE graph highlight WOA's potential appropriateness for situations requiring accurate forecasts with few mistakes. And also WOA reduces prediction mistakes by decreasing the square root of the average squared differences between predicted and actual values.

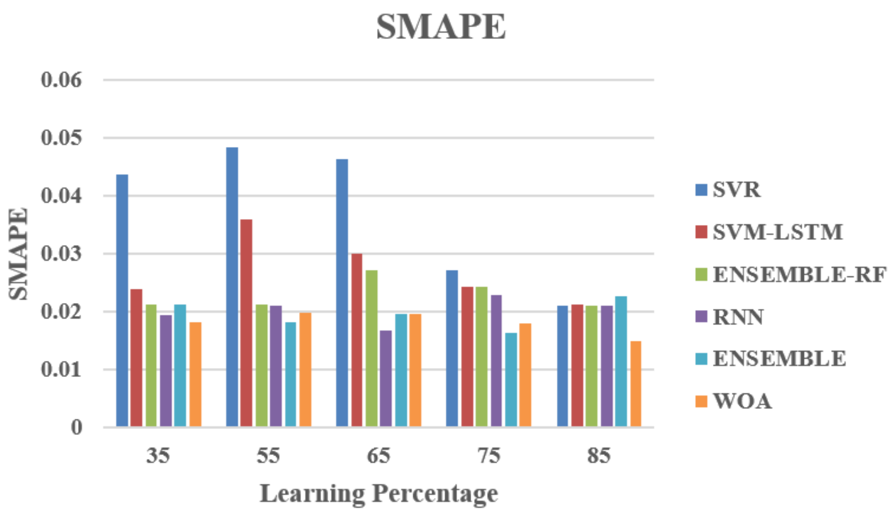

Figure 9.
SMAPE.

The graph shows the Symmetric Mean Absolute Percentage Error (SMAPE) numbers, which show how accurate different methods are at various percentages: 35%, 55%, 65%, 75%, and 85%. A lot of people use SMAPE to figure out how accurate predictions are as a percentage. In this situation, the Walrus Optimisation Algorithm (WOA) consistently does a great job, as shown by its consistently low SMAPE numbers at all SVR percentages. At 85% SVR, WOA gets an excellent SMAPE of 0.014932407, which shows that it is good at making correct guesses with low percentage mistakes. When compared to other algorithms, WOA is shown to be reliable and good at catching the variability of the information. This makes it a good choice for situations where accurate predicting is needed. This shows WOA's accuracy in predicting tasks, making it ideal for accurate forecasts.

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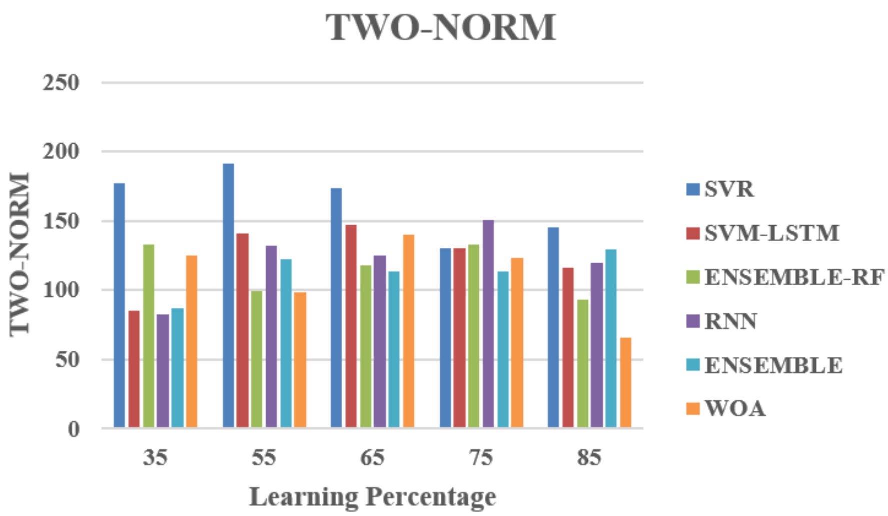

Figure 10.
Two norm.

From the above graph it is observable that Two-Norm values on the graph illustrate algorithm performance at 35%, 55%, 65%, 75%, as well as 85%. The Two-Norm employs the Euclidean norm to calculate error magnitude. The Walrus Optimization Algorithm (WOA) produces low Two-Norm values consistently across all SVR percentages, exhibiting competitive performance. The WOA Two-Norm of 65.98940214 at 85% SVR demonstrates its capacity to decrease prediction errors. When compared to other algorithms, WOA demonstrates its robustness and efficacy in capturing dataset heterogeneity. WOA's Two-Norm graph trends indicate that it may be appropriate for instances when error reduction is crucial.

5.1. Comparision the Proposed Model with Existing Models

	Esemble	CNN	SVM
MAE	2.3	3.75	4.1
RMSE	5.19	6.8	7.5
MSE	3.11	4.2	4.75

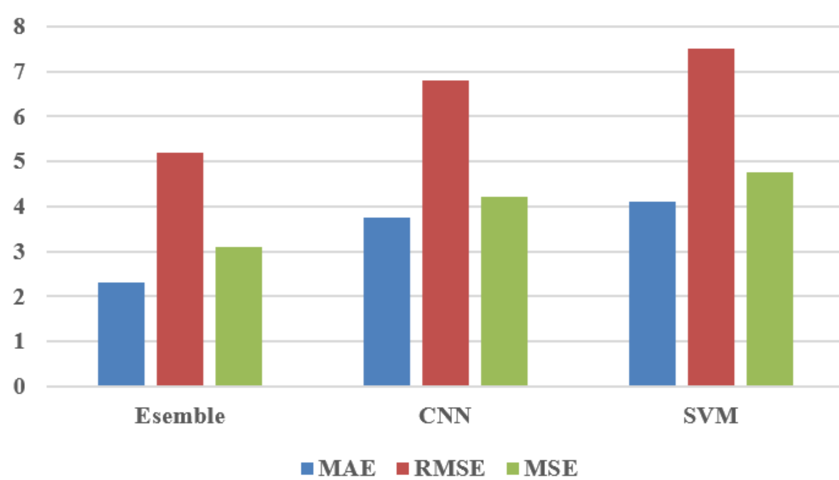

Figure 11.

We compared our Ensemble model enhanced with the modified Walrus Optimization Algorithm (WOA) for Quality of Service (QoS) prediction to conventional models like Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) using MAE, RMSE, and MSE. All measures showed that our model predicted service quality well. The Ensemble model with WOA has a lower MAE of 2.3 than CNN and SVM, suggesting more accuracy and less divergence from real values. Compared to CNN and SVM, our model's RMSE value of 5.19 was much lower than 6.8 and 7.5, indicating improved prediction errors and precision. Our model has a lower MSE (3.11) than CNN (4.2) & SVM (4.75), suggesting better squared error reduction. Our approach provides more accurate and dependable service quality forecasts than previous techniques, which might improve network management as well as user experience in dynamic mobile network settings.

6. Conclusion

The Ensemble-Based Service Quality Prediction (EAQP) model, which is reinforced with the cutting-edge Walrus Optimization Algorithm (WOA), exhibits exceptional performance when it comes to predicting service quality in settings composed of dynamic mobile networks. WOA's flexibility enhances accuracy across a variety of assessment criteria, which allows the model to make strong predictions. This is accomplished by the rigorous pretreatment of data and the integration of a wide variety of machine learning techniques. A number of metrics, including an MAE of 2.301794167, MASE of 3.111924686, MEP of 1.476953076, One-Norm of 199.8951208, RMSE of 5.194432863, SMAPE of 0.014932407, and Two-Norm of 65.98940214, are among the metrics that WOA obtains low values for when it has an SVR of 85%. These discoveries not only contribute to the advancement of research approaches in the field of machine learning, but they also have major practical consequences for enterprises that are dependent on mobile network services. Increasing customer happiness and improving service delivery tactics are both possible outcomes of enterprises' ability to properly forecast service quality and proactively handle network problems. Due to the fact that the model can be used in a variety of network scenarios, it has the potential to be a very useful instrument for industry practitioners who are looking to enhance both the quality of service and the user experience. At last the Comparision of proposed model with existing models also dive into the novelty of our proposed and by this we can conclude that the proposed model is best suitable for real-time Quality of Service predictions

6.1. Real World Applications and Implications

The Ensemble-Based Quality of Service Prediction model with Walrus Optimization has great promise for mobile networks and service quality prediction. Telecommunications firms looking to improve service quality evaluation might use this novel technique. This approach may help network operators discover and resolve problems like latency in the network, bandwidth availability, as well as connection stability before they affect user experience by correctly forecasting service quality indicators. The model's Walrus Optimization Algorithm for feature selection provides scalability and flexibility for changing network situations. Beyond telecommunications, the model's ensemble learning architecture and optimization approaches are applicable to healthcare, banking, and environmental monitoring. The approach might change service quality prediction, providing industry experts and researchers with realistic answers.

6.2. Limitations

Ensemble models like GRU, LSTM, Random Forest along with WOA Optimization may improve prediction accuracy, but they have limitations. Integrating learning algorithms may slow real-time applications or resource-constrained devices. Selecting hyper parameters and optimization techniques for each component model is challenging due to the highly dimensional parameter space & probable model interactions, yet the ensemble model's effectiveness relies on it. Stakeholders struggle to understand and trust ensemble models like models based on deep learning, which are black boxes. Scalability of the ensemble approach may be limited for large datasets or high-dimensional features spaces, requiring careful processing resources as well as algorithmic efficiency.

6.3. Potential Challenges for Implementation

Ensemble models using voting classifiers and Walrus Optimization Algorithm (WOA) feature selection may have difficulties. Coordinate and test data preprocessing, feature selection, ensemble construction, and optimization for model integration and interoperability. To identify the optimum techniques and hyper parameters, performance may need extensive tweaking and experimentation, adding complexity as well as duration to development. The proposed method may need scalable algorithms and networked computer infrastructures to evaluate enormous volumes of data. Reliable validation and evaluation of the ensemble model's generalization accuracy and dependability across datasets and application contexts need rigorous experimental design & statistical analysis.

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