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Intelligent Hotel Recommendation Engine Using Lstm And Hippopotamus-Inspired Hyperparameter Tuning

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Abstract. *Recommendation system has gained a lot of popularity in almost all the fields. Hospitality industry has transformed with the gain in popularity of recommendation system. Hotel industry has boomed a lot, as users are getting ample recommendation options depending on their preferences and choices. In this study we have used Long short Term Memory model (LSTM)for hotel recommendations and to increase the accuracy of recommended hotels we have used Hippopotamus Optimization Algorithm (HOA) based on user's personal preferences. LSTM analyse user's reviews to understand their preferences for making personalized recommendations. HOA is used to fine tune the hyperparameters of LSTM to give better personalized recommendation which matches user's choice. This hybrid model gives training accuracy of 97.69% and 0.2830 loss. Validation accuracy of 93.21% and loss of 0.3016. HOA+LSTM model beats classic optimisation techniques, offering a more resilient and reliable recommendation system. This research presents a sophisticated optimisation method that enhances decision-making for users in intelligent tourism.*
Key words. *Long Short-Term Memory model; Hippopotamus Optimization Algorithm; Hyperparameter Tuning; Hotel Bookings; Location-based Recommendation system; Hotel Reviews*

1. INTRODUCTION.

Drastic influence of Digital technologies have transformed the way tourists book accommodations. Location-based hotel recommendation systems offer personalized recommendations based on facilities, conveyance. These systems analyze travel purposes and hotel locations, ensuring accuracy, flexibility, and benefit for both guests and hotels [1]. However, researchers need fast data anonymisation with federated learning algorithms, evaluating travel duration, user interests, location, society, and contextual information. The system must be scalable, despite real-time responses and cold starts, and can't agree on location-based hotel recommendation system metrics. Researchers must work with data scientists, machine learning experts, privacy lawyers to improve user experiences[2-5]. Complex algorithms that satisfy every visitor needs, are personalized, privacy-aware, and address these difficulties can be created, and the hospitality industry is increasingly appreciating these systems [6-7].

1.1 Problem Formulation.

Aim of LSTM is to recommend hotels based on user's budget, preferences, facilities, and nearby landmark distance. Real-time location data refines searches, while proximity-based suggestions prioritize hotels near key sites. Booking time, season, duration of stay, and local event affect availability and pricing. Machine learning models improve suggestion accuracy over time. Addressing privacy issues and focusing on individual qualities can improve customer satisfaction.

2. Related Work. Xiong and Geng et al. (2010) reviewed online hotel booking systems like Elong, Ctrip, Qunar, and Kuxun. They developed a tailored online hotel marketing system using a polymerisation model, online shopping habits, and a Matlab program for personalized recommendations.

Chang et al. (2013) demonstrate a PA system that effectively recommends hotels based on user recommendations. The system considers factors like location, nearby restaurants, user ratings, and reviews. Experiments confirm the system's effectiveness in recommending hotels, with the best options chosen based on user preferences.

Sharma et al.'s multi-criteria recommendation system (2015) allows customers to choose the best hotel based on their preferences and user reviews. The system uses Natural Language Processing algorithms and addresses issues with cold start and language in text messages.

Song et al. (2017) propose a method that combines collaborative filtering with data classification, evaluating its accuracy using hotel suggestions data. The top-3 and Top-10 recommendation lists were found to outperform the top ten lists under cold start conditions, using ROC curves and a 10-fold cross-validation approach.

Chang et al. (2018) propose a Twitter-based recommendation engine that considers user preferences and personal data. They extract hotel information from Yelp and analyze user behavior on social media. Their strategy could increase RECALL accuracy by 30%, accuracy rate to 100%, and mean reciprocal rank accuracy to 80% compared to a Twitter-based recommendation system that did not consider diverse social media.

Bodhankar et al. (2019) highlight the rise of recommendation systems as an alternative to traditional services due to technological advancements. These systems focus on practical and personalized services, with collaborative filtering being a key tactic in providing consumers with necessary information.

Kashef (2020) proposes a clustering-based approach using the information retrieval vector space model to provide accurate suggestions. The method uses four popular clustering algorithms: k-means, fuzzy c-mean, single-linkage, and self-organising maps. The system's efficacy is evaluated using seven IoT rating datasets. The algorithm outperforms conventional collaborative filtering in error and prediction metrics, and the self-organising strategy yields more accurate recommendations compared to partitional learning approaches.

Sharma et al. (2021) use Airbnb data and explainable machine learning to address two challenges in big data marketing. They compile a list of potential influences on product price and customer satisfaction, including bedroom size, host status, and reaction rate. They construct and evaluate a prediction model, which could help find decision-making applications for explainable algorithms, a hot topic in the industry.

Le et al. (2022) propose a novel collaborative filtering approach for hotel sector multi-criteria recommendation. The approach uses a deep learning model with matrix factorisation for multi-criteria rating prediction, considering user preferences across multiple dimensions. The Dempster-Shafer theory of evidence is used to represent ratings as mass functions, and evidential reasoning is employed to consider their uncertainty. The recommendation rating is determined by summarizing all ratings using Dempster's rule of combination. Experiments on a real-world dataset show the proposed solution is more effective and efficient than previous multi-criteria collaborative filtering systems.

Dowlut and Gobin-Rahimbux (2023) discuss the use of Deep Learning for OR prediction, examining recent developments from 2017 to 2022. They provide insights on variables, prediction methods, and assessment criteria. The Snowballing approach was used for the SLR, with fifty papers selected for analysis. Five variables were identified, and deep learning's long short-term memory (LSTM) algorithm was commonly used. MAPE was the most important performance factor, and further research is needed to fully understand the accuracy-enhancing potential of the CNN-LSTM hybrid model.

Patel et al. (2023) provide a machine learning-based hotel recommendation system that considers customer reviews and offers personalised hotel choices. By analysing review content using TF-IDF processing methods, the system can accurately forecast user preferences and provide reliable hotel suggestions. Travellers may gain from the suggested additional tree-based approach if it leads to more targeted and personalised hotel suggestions.

Contessa et al. (2024) developed a two-stage method using historical and prospective booking information. They used Principal Components Analysis (PCA) to combine patterns in booking curves. The method outperformed clustering-based and conventional additive pickup methods in three European hotels from 2018-2022. PCA-based methods performed better regardless of the hotel or forecasting horizon. Incorporating ADR in PCA could improve daily hotel demand estimations.

Rajput et al. (2024) propose a deep learning strategy for multi-criteria recommender systems, combining matrix factorisation and deep autoencoders to improve accuracy. Theapproach, tested on the Yahoo! Movies multi-criteria dataset, yields more tailored recommendations than current algorithms and can reduce data sparsity by up to 11 percent. The study's experimental results demonstrate the potential of this approach in enhancing recommendation accuracy.

3. MATERIAL AND METHOD.

3.1. Dataset. The dataset which we have used in our study was European hotel dataset sourced from Kaggle. This dataset is scrapped from Bookings.com comprises of 515,738 customers reviews and other details for 1,493 luxury hotels. This dataset also includes the geographical coordinates of hotels for accurate findings. Dataset has total 17 attributes out of which 9 were used in our experiment. Data pre-processing involves eliminating incomplete and noisy data to cleanse and prepare it for further operations[8-10]. The data utilised in our study contains anomalous text that requires cleansing. Datasets might vary in format depending on their intended use. We typically input the data into a comma separated values (CSV) file. Our approach is built in Python, a high-level programming language that offers numerous packages to handle dataset efficiently. These packages can streamline data processing, hence enhancing efficiency. Furthermore, it possesses numerous exceptional libraries for data analysis. Python is capable of managing extensive datasets and facilitates the implementation of automated analysis with greater ease. The pre-processing encompasses data integration, elimination of missing values, removal of stop words, conversion to lowercase, tokenisation, extraction of special characters and numbers, parts of speech tagging, lemmatisation, among others[13-16].

3.2. Method. LSTM networks are a powerful deep learning approach that improves long-term behavior and preference prediction in location-based hotel recommendation systems. These networks provide personalized suggestions based on a user's past data and location, tracking reservations, ratings, and reviews to match suggested hotels to user needs. They estimate travel and offer accommodations based on prior journeys' destinations and lodgings using real-time location data[17-21]. The model considers hotel quality and satisfaction, using repeated user ratings and evaluations to enhance proposals. Time-related input sequences improve prediction accuracy. The metaheuristic optimization algorithm HOA combines exploration and exploitation to avoid local minimums and explore solution space worldwide. It balances exploration and exploitation hierarchically, reducing computing overhead and improving hyperparameter combinations. HOA is better suitable for global optimization than PSO or GA[22-26]. It can adapt to changing surroundings, reduce time complexity, and train large-scale recurrent LSTM networks faster than grid search. HOA surpasses PSO and enhanced genetic algorithms in accuracy and training time[27-29].

3.2.1. PROPOSED METHODOLOGY:

Step 1 Input Layer

- Sequences represent user interactions (e.g., bookings, ratings, reviews).
- Incorporates location data (historical and real-time).
- Uses temporal data (time of booking, seasonality).
- Considers contextual factors like: Weather conditions, Local events, Proximity to points of interest
- Key inputs: Historical user behavior, Geographical information, Time-based patterns, Context-specific events and conditions

$$X = \{x_1, x_2, ..., x_T\} \quad \text{.............................(1)}$$

- Where each x_t is a feature vector at time step t

Step 2 Embedding Layer

- Categorical inputs (e.g., hotel IDs, location codes) are used.
- Embedding layer transforms these into dense vectors.

$$\text{Embedding}(x_t^{\text{cat}}) = W_e \cdot x_t^{\text{cat}} \quad \text{....................(2)}$$

- Where W_e : learnable embedding matrix
- x_t^{cat} :one-hot encoded categorical input
- Embeddings capture relationships between categories.
- Step 3 LSTM Layers
- Core of the model: LSTM layers for sequence processing.
- Captures temporal dependencies in user behavior.
- Forget Gate:
- First LSTM layer learns short-term patterns (e.g., recent interactions, travel locations).

$$\boldsymbol{f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)} \quad \text{....................(3)}$$

- Input Gate:

$$\mathbf{i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)} \quad \text{................................(4)}$$

- Stacked LSTM layers capture long-term dependencies.
- Candidate Cell State:

$$\mathbf{c_t = tanh(w_c[h_{t-1}, x_t] + b_c)} \quad \text{......................(5)}$$

- Cell State Update:

$$\mathbf{c_t} = \mathbf{f_t} * \mathbf{c_{t-1}} + \mathbf{i_t} * \mathbf{\bar{c}_t} \quad \text{......................(6)}$$

- Helps retain earlier sequence information for better trend understanding.
- Learns both recent and broad user behavior patterns.

Step 4 Dense Layers

- Output from LSTM layers is passed to dense layers.
- Dense layers combine learned features into a final representation.
- Final representation captures user preferences and current context.

$$\mathbf{y} = \boldsymbol{\phi}(\mathbf{w_d} \cdot \mathbf{h} + \mathbf{b_d}) \quad \text{.............(7)}$$

- where w_d: dense layer weights
  ϕ: Sigmoid Activation Function
- Final representation captures user preferences and current context.
- This representation is used to generate hotel recommendations.

Step 5 Hippopotamus Optimization Algorithm (HOA)

- HOA is used to optimize LSTM hyperparameters during training.
- Exploration:

$$X_i^{t+1} = X_i^t + r_1 \cdot (X_{\text{best}}^t - r_2 \cdot X_i^t) \quad \text{.....................(8)}$$

- Exploitation:

$$X_i^{t+1} = X_i^t + r \cdot (X_{\text{best}}^t - X_i^t) \quad \text{...............................(9)}$$

- Step 6 Output Layer
- Final dense layer outputs scores.
- Each score shows hotel relevance for the user.
- Hotels are ranked by score.

$$\hat{y}_i = \text{Score for hotel } i \quad \text{..(10)}$$

- Top hotels are recommended.

Step 7 Loss Function and Optimization

- LSTM uses loss functions like Cross-Entropy (for classification).

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \cdot \log(\hat{y}_i) \quad \text{.............................(11)}$$

- HOA optimizes LSTM's hyperparameters.

Step 8 Training and Evaluatio

- Uses historical user data for training and validation.
- HOA optimizes LSTM hyperparameters during training.
- Ensures good generalization to new data.
- Evaluated using accuracy, precision, and recall.

Fig. 3.1. show the flow of the proposed algorithm. LSTM is used as a base model and hippopotamus optimization algorithm is used for the optimization of hyper parameters. LSTM model performance is highly dependent upon the tuning of hyperparameters. HOA helps us to achieve the optimized value of hyperparameter after tuning.

The Hippopotamus Optimization Algorithm (HOA) is essential for enhancing this process by optimizing the hyperparameters of the LSTM network during model training. The HOA functions by initializing a population of candidate solutions, each embodying a set of hyperparameters, and systematically refining them based on their efficiency on the validation dataset. This emulates hippopotamuses' social and adaptive behaviours, enabling the algorithm to effectively navigate the solution space and settle on the optimal hyperparameter set to enhance model performance. The model's ultimate result is a recommendation score for each hotel, meticulously ranked to provide the user with the most appropriate accommodations. To finalize the process, the model undertakes a stringent training and evaluation phase, employing past user data to further improve the LSTM's hyperparameters, ensuring that the model achieves high accuracy, precision, and recall while adapting effectively to novel, unseen data. The HOA-

LSTM model is a robust and unique instrument that enhances the effectiveness and precision of hospitality services through a complete and dynamic approach[29-30].

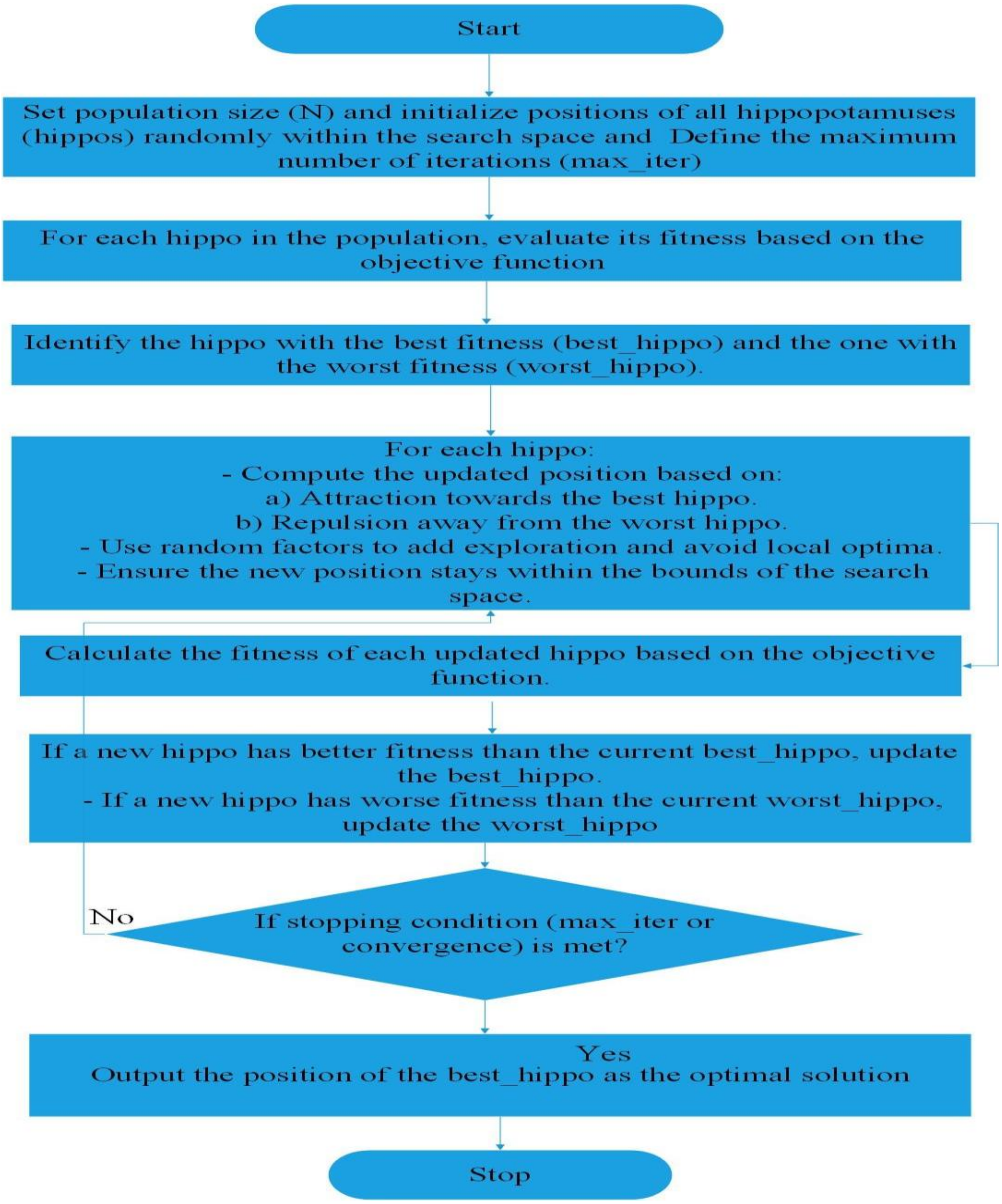
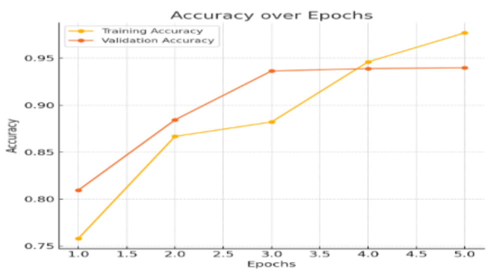


Fig. 3.1. Work Flow of Proposed Algorithm

4. RESULTS AND ANALYSIS.

Fig 4.1 demonstrates the Optimized LSTM Model Accuracy.



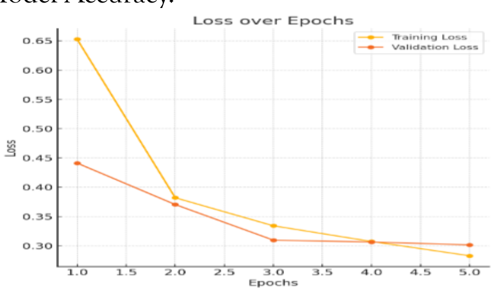


Fig. 4.1. Optimized LSTM accuracy Fig. 4.2. Optimized LSTM Model Loss

The optimised LSTM model improves accuracy over time shown in figure 4.1. A well-generalized model that balances fitting training data with performing on unseen data has near training and validation accuracy by the last epoch. Fig 4.2 demonstrates the Optimized LSTM Model Loss.

The Hippopotamus Optimisation Algorithm (HOA) adjusted the LSTM model in fig. 4.2 by reducing loss and validation loss. The gap between training and validation loss rises in later epochs, proposing regularisation or early termination to prevent overfitting and boost generalisation on unknown data. In real-world machine learning applications, this approach balances model performance with dataset longevity.

Table 1 Performance of the proposed model

S.No.	Epoc	accuracy	loss	val_accuracy	val_loss
1	1/5	0.7581	0.6529	0.8095	0.4413
2	2/5	0.8667	0.3821	0.8843	0.3705
3	3/5	0.8821	0.3342	0.9364	0.3097
4	4/5	0.9461	0.3074	0.9389	0.3065
5	5/5	0.9769	0.2830	0.9397	0.3016

The Hippopotamus Optimisation Algorithm enhanced the hotel booking LSTM model in Table 1. In the first epoch, the accuracy was 75.81% and the model loss was 0.6529. Results improve with 80.95% accuracy and 0.4413 validation loss. In epoch 2, accuracy reached 86.67% and loss dropped to 0.3821. Training accuracy steadily increases to 98% by the fifth epoch. Validation accuracy spikes at first, then plateaus at 94% after the third epoch. Consistently decreasing training loss indicates efficient model learning. Validation loss reduces steadily, showing good model generalisation without overfitting. Consistent improvement in training measures indicates good model training. The peak in validation accuracy and the small difference between training and validation metrics indicate that the model is performing well with the current setup.

Fig 4.3 demonstrates Optimized LSTM Model Performance

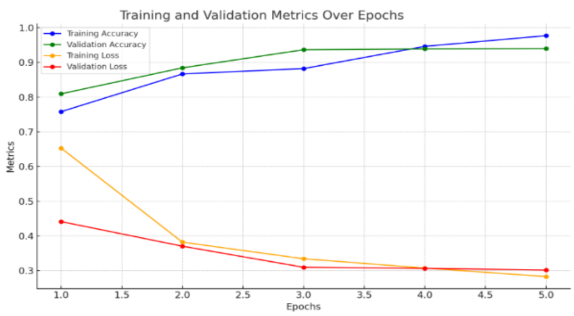


Fig. 4.3. Optimized LSTM Model Performance

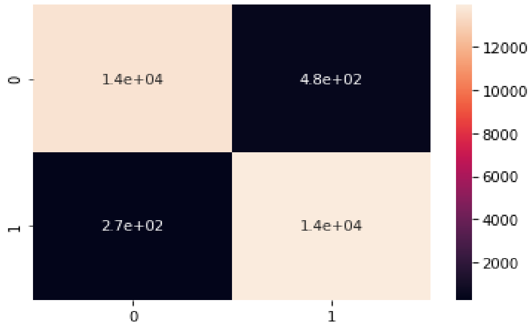


Fig. 4.4. Optimized LSTM Model Confusion matrix

The Hippopotamus Optimisation Algorithm (HOA)-tuned LSTM model has shown promising results in training and validation datasets, with increased accuracy and stable validation accuracy. This indicates the model's ability to recognize hotel review data trends and produce accurate suggestions. The model balances learning from training data and generalizing to new data, demonstrating its effectiveness in real-life situations.

The confusion matrix in Figure 4.4 shows the model's performance on European hotel reviews-based booking recommendations. The model's accuracy in true positive and negative predictions makes it reliable and useful in real-life scenarios. However, it requires fine-tuning or data analysis for common false positives or negatives. HOA LSTM network tuning reduces classification mistakes, boosting hotel booking recommendations.

Scalability and computational speed are crucial for manipulating hotel booking recommendation data. The HOA algorithm reduces computational expense by minimizing redundant evaluations during optimization processes, improving training examples by speeding up convergence to perfect hyperparameters. The model's scalability was tested using 10,000 to one-million hotel reviews, showing linear scalability with dataset size.

CPU and memory usage were monitored during training, with an Intel Core i9 Processor 64GB RAM used. Processing in batches helped with model size, allowing the model to run on more data without running out of memory. These findings demonstrate that the HOA-optimized LSTM model is computationally efficient and scalable, making it suitable for encyclopaedic hotel booking recommendation systems. It is practical in situations where untrained data is still needed and fast recommendations based on historical transaction logs are needed.

4.1. DISCUSSION.

The Hippopotamus Algorithm (HOA) is a machine learning algorithm that optimizes LSTM networks, enhancing model performance and accuracy. It outperforms grid search and random search in convergence and model accuracy. HOA-tuned LSTM improves validation dataset accuracy by 4.7%. It outperforms Grid Search and Bayesian Optimisation in convergence and model accuracy. The HOA-tuned model optimizes the optimal hyperparameter configuration 30% faster than Grid Search and Bayesian Optimisation, benefiting real-world situations with limited processing resources. The model's suggestion accuracy was tested using European hotel reviews, showing improved precision, recall, and F1-score. The HOA-optimized LSTM sentiment analysis and user preference identification improve user satisfaction and recommendation system trust. The model showed linguistic and multicultural adaptation across datasets, making it suitable for large-scale European recommendation systems.

Table 3 shows the result comparison achieved by various traditional machine learning models and Deep learning with the proposed model as shown below.

Table 3Comparison of the proposed model with other ML & DL Algorithms

Technique	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
K-Nearest Neighbors (KNN)	72	74	70	72
Support Vector Machines (SVM)	78	80	76	78
Gradient Boosting (e.g., XGBoost)	86	88	84	86
Random Forest (RF)	82	83	81	82
Artificial Neural Networks (ANN)	90	87	84	85
LSTM	89	89	86	87
Proposed Model	93	92	95	93

4.2. Limitations and Practical Implications. The Hippopotamus Optimisation Algorithm (HOA) and Long Short-Term Memory (LSTM) networks have been used to enhance the accuracy and reliability of LSTM networks. HOA efficiently investigates LSTM networks with high-dimensional, non-convex hyperparameters, potentially leading to better restaurant and tourism recommendations. HOA-trained LSTM models improve customer review analysis and emotion detection, outperforming standard models on various hotel review data subsets. The algorithm's balanced exploration and exploitation minimize search process stagnation at local minima, making hyperparameter adjustment necessary for maximum performance. HOA-tuned LSTM models can predict user preferences from textual reviews, improving satisfaction and loyalty, and making hotels' products more relevant and effective. This study suggests that HOA could be used in health, social media, and financial applications of LSTM networks, potentially inspiring natural pattern-based optimization strategies. Future studies should use other datasets or incorporate user demographics or booking history.

Conclusion and Future scope. The Hippopotamus Optimisation Algorithm (HOA) and LSTM networks were used to improve hotel booking recommendations using unstructured hotel review data. The HOA-tuned LSTM model outperformed traditional methods in prediction accuracy and reliability. The algorithm efficiently explored and exploited hyperparameter search space, enhancing the LSTM model. As the model recommended hotels more accurately, user happiness increased. The successful use of HOA opens up new applications in other domains using LSTM networks and similar deep learning models, suggesting its adaptability and efficacy in large, complex datasets.

5.1. Future scope. The Hippopotamus Optimisation Algorithm (HOA) is promising for recommendation system research and implementation, potentially enhancing recommendation accuracy by incorporating deep learning architectures like Transformer models. Future studies could incorporate non-European hotel reviews, multilingual reviews, and diverse datasets to improve HOA's cultural and linguistic optimization efficiency. The Hippopotamus Optimisation Algorithm and LSTM networks can enhance hotel recommendation systems by considering user demographics, booking history, and hotel quality. This approach can also improve real-time recommendation systems by processing multiple data types. Future research should focus on scalability, integration, and UI design, as well as user research on model recommendations. The ethics of AI-driven recommendation systems should be considered, with future research evaluating fairness, openness, and accountability. Developing audit methods could enhance user trust. The success of this method in improving hotel booking recommendations using European reviews opens new opportunities for AI-driven suggestions.

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