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Optimizing LSTM Networks with Hippopotamus Optimization Algorithm for Enhanced Hotel Booking Recommendations Based on Hotel Reviews[1]

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Abstract

The fast growth of Europe's hospitality business has given travellers an overwhelming number of hotel options, needing advanced recommendation systems. This study uses the Hippopotamus Optimisation Algorithm (HOA) to tune Long Short-Term Memory (LSTM) networks to improve hotel booking recommendations based on user evaluations. The LSTM network analyses massive volumes of unstructured textual data from hotel reviews to understand traveller attitudes and preferences and make personalised suggestions. The HOA optimises LSTM network hyperparameters for better prediction performance than standard techniques. A large European hotel review dataset shows that the proposed approach accurately recommends hotels that match user preferences. The final epoch of the proposed model had 0.2830 loss and 97.69% accuracy. Validation loss 0.3016, accuracy 93.37%. Despite its excellent training accuracy, the model's constant validation accuracy and a bit higher validation loss may prevent generalisation and overfitting. The HOA-tuned LSTM model outperforms conventional optimisation methods, providing a more robust and trustworthy recommendation system. This research introduces an advanced optimisation technique that improves European travellers' decision-making in intelligent tourism.

Keywords

Long Short-Term Memory (LSTM) networks; Hippopotamus Optimization Algorithm; Hyperparameter Tuning; Hotel Booking; Location-based Recommendation system; Hotel Reviews.

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1. Introduction.

Digital technology's rapid growth has changed hotel room booking. Tourists are having trouble selecting hotels that match their needs due to the limitless amount of possibilities. This challenge inspired location-based hotel recommendation systems to help tourists choose. Location-based hotel recommendation systems use consumer preferences and geographical data to propose hotels to travellers. These methods consider amenities, transportation, and atmosphere. When integrated, location-based systems can give passengers personalised recommendations based on tastes, cost, and star rating. Convenience matters when choosing a hotel. Vacationers may prefer beaches and cultural places, but business tourists may prefer conference centres and corporate offices. For these needs, location-based recommendation systems analyse the user's travel purpose and hotel location. To balance human preferences and objective data, algorithms need frequent adjustments, like a perfect neighbourhood. Vacation planning is more customised with location-based hotel recommendations. These algorithms improve accommodation selection by considering location and traveller interests. Since these technologies are used in holiday planning, they may improve accuracy, flexibility, and usefulness. This technology enables hotels to understand guests' preferences and tailor service. This innovation streamlines hotel selection for guests and hotels [1].

The hotel business is adopting location-based recommendation systems because they offer guests personalised options based on their current or prospective location. These systems can improve user experiences, but they must overcome numerous research difficulties to become more accurate, efficient, and scalable. Multiple heterogeneous data sources make location-based hotel recommendation systems difficult to construct. Each network shares hotel information, reviews, and GPS locations. Social media, travel websites, and user reviews provide data. Keeping this data clean [2], coherent, and integrated is difficult. Format, quality, and detail of data sources make guideline harmonisation challenging. Location data threatens privacy. Location data may be withheld to prevent exploitation or theft. Data privacy laws like GDPR make recommendation system accuracy and customisation challenging. Researchers need federated learning algorithms to anonymise data without delaying the system. Travel duration, user interests, geography, and society strongly influence hotel choices. These environmental components are hard to document and understand. Business or pleasure travel may change a user's favoured hotel category. The recommendation system must explain and include this contextual information to provide suitable options. Scalability is important for hotel recommendation systems that serve hundreds of hotels and millions of customers [3-6]. To generate timely recommendations, the system must quickly process massive data sets. Cloud solutions, distributed computing, and efficient algorithms enable scalability. Answers in real-time while meeting computational needs are difficult. Cold start issues can arise when working with unskilled consumers or hotels without enough historical data. The algorithm struggles to offer suggestions with insufficient data. One novel method is to infer user preferences from social media profiles. Hybrid recommendation models using content-based algorithms and collaborative filtering are another alternative. Changes in user experiences, life events, and personal tastes are among the numerous reasons preferences change. The recommendation models must be adjusted to reflect these changing tastes. Adaptive models and learning algorithms keep suggestions relevant and user-specific. Researchers struggle to agree on a reliable metric for location-based hotel recommendation systems. In practice, accuracy and precision may be too optimistic or pessimistic about the system's capabilities. Researchers should create new location-based recommendations, user enjoyment, and system adaptability metrics. User research and qualitative comments are needed to verify the system's efficacy [7].

When users' locations determine real-time idea delivery, things get much more problematic. Recommendation creation, database querying, and location data processing should be fast. Only by improving data processing pipelines and algorithms is this achievable. Due to network delays or interruptions, the algorithm may lose time from suggestions. When creating international location-based hotel recommendation systems, cultural differences must be considered. Nationality, geography, and culture can greatly affect hotel guests' preferences. Cultural intricacies must be included in the recommendation algorithm to deliver good ideas to people from all backgrounds. This needs knowledge of the target culture and the ability to incorporate cultural elements into the proposal. Before location-based hotel recommendation systems can improve user experiences, various research challenges must be overcome. Data scientists, machine learning experts, privacy lawyers, and cultural studies scholars must collaborate to overcome these issues. If scholars keep studying these issues, locationbased hotel recommendations will use more complex algorithms that are personalised, privacy-aware, and able to fulfil global visitor needs. The hospitality sector is increasingly recognising the value of location-based hotel recommendation systems. These systems provide personalised suggestions to enhance client experiences [8-10].

1.1. Problem Formulation.

The hardest part of location-based recommendation systems is choosing the right hotels. Common input criteria include user preferences, budgets, facilities, and landmark distance. Hotel guests require real-time location data to refine their search. Our goal is to prioritise hotels that suit user needs by assessing and processing these factors. Hotels' star ratings, user-requested budgets, and facilities like free Wi-Fi, breakfast, and pools are considered. Understanding user preferences helps determine suggestion relevance. Proximity-based suggestions require the user's specific location. To enhance convenience and decrease travel time, nearby hotels are prioritised. This category considers hotels' proximity to key sites, business districts, and entertainment destinations. This is crucial for clients who value their time and want to limit travel between their accommodations and critical venues. Booking time and length of stay affect hotel availability and pricing. Consider these: seasonal trends and local events affect hotel demand and client preferences. We may eliminate bad hotel choices by analysing guest reviews on service and quality. A better-rated hotel is more likely to please guests [11].

Multi-criteria decision-making (MCDM) processes are usually used to balance all relevant inputs when posing a problem. Hybrid, content-based, and collaborative filtering algorithms are popular. These algorithms produce hotel recommendations based on input parameters, similar user preferences, and prior behaviour. Training machine learning models on user interactions can improve suggestion accuracy over time. Because input elements like real-time location and hotel availability change, location-based hotel suggestions are challenging to create. The system must handle changes quickly.

By addressing location data privacy issues, we may regain users' trust while complying with data protection laws. A well-formulated challenge for locationbased hotel recommendation systems should include user preferences, real-time location, POI proximity, temporal considerations, and user reviews. These algorithms deliver personalised hotel recommendations by focusing on individual qualities. The goal of using complicated algorithms and machine learning models to improve these recommendations is customer happiness [12].

1.2. Research Contributions

Hybridizing the Hippopotamus Optimization Algorithm (HOA) with LSTM, a famous gradient boosting technique, to accurately recommend hotels can lead to various research advances:

- Integrated Hippopotamus Optimization Algorithm (HOA) for fine-tuning LSTM hyperparameters, significantly improving recommendation accuracy in this work.
- In this paper, the Hippopotamus Optimization Algorithm (HOA) swiftly searches the search space while LSTM learns from data to produce accurate predictions.
- Using LSTM's feature importance, the hybrid technique has chosen features effectively.
- In this paper, the authors focused on location-based recommendation by finding the most important features, enhancing accuracy and interpretability and achieving an accuracy level of 97.69.
- While feature significance gives LSTM some interpretability, hybridizing it with Hippopotamus Optimization Algorithm (HOA) can improve it.

The complete research is organized as follows. Section two reviews and compares existing research in location-based recommendation systems. Section three presents materials and methods, covering the details of existing processes and architecture, features of a proposed hybrid model, and dataset description. Section four covers the practical information, simulation parameters, data pre-processing, simulation results, and the results and discussion to justify the research. The last section, five, covers the conclusion of the proposed location-based recommendation system and suggests its limitations and future direction.

2. Literature Review

A system that successfully recommends hotels based on user recommendations is shown by Chang et al. (2013). The majority of hotel recommendation systems use rating and price—two metrics that have nothing to do with location—to make suggestions. The hotel's location of local restaurants and entertainment venues is another factor we take into account when recommending it. Before choosing a hotel to stay, we always look at the surrounding region. The user's previous ratings of the hotel are next taken into account. We can tell what they like by reading their review. In the end, we pick the best k hotels based on how similar they are to the user's preferences. Experiments confirm the effectiveness of our method. When asked to recommend hotels to users, our system performs adequately, according to the experimental results.

Using the multi-criteria recommendation system for hotels proposed by Sharma et al. (2015), customers can select the top hotel in a city based on their preferences and the reviews of other users. We used a user-item-feature database that we constructed using various Natural Language

Processing algorithms applied to a Hotel Review Corpus to learn how past customers rated the hotel on various criteria. In addition, it tackles the cold start problem and the language issue with text messages for this site when it comes to user review harvesting.

An enhanced approach is suggested by Song et al. (2017), which merges collaborative filtering with data classification. The suggested method is evaluated using data on hotel suggestions. By examining the ranks, you may determine the accuracy of the advice. The top-3 and Top-10 recommendation lists accuracy is investigated using ROC curves and the 10-fold cross-validation approach. According to the results, the top three hotel recommendation lists from the combined method outperform the top ten lists when evaluated under cold start conditions.

Using data from multiple social media sites, Chang et al. (2018) suggest a recommendation engine that runs on Twitter. We start by building a model that accounts for user preferences and personal data to enhance matrix factorisation. Next, we extract some basic hotel information from Yelp and add it to our model. However, we did figure out a technique to analyse user conduct on social media and build vectors of user posting behaviour using their previous tweets and Yelp ratings. If compared to a recommendation system based on Twitter that did not take diverse social media into account, the suggested strategy might increase RECALL accuracy by 30%. The accuracy rate might go up to 100% and the mean reciprocal rank accuracy could go up to 80%.

According to Bodhankar et al. (2019), a recommendation system has emerged as an alternative due to technological improvements. Practical and personalised services are the backbone of recommendation systems, which aim to provide consumers with the information they need. The most important tactic in this field is collaborative filtering. An improved to make hotel and traveller recommendations, this article presents a collaborative filtering approach.

Using the information retrieval vector space model, Kashef (2020) suggests a clustering-based approach to deliver very accurate suggestions. The described approach incorporates four popular clustering algorithms: k-means (KM), fuzzy c-mean (FCM), single-linkage (SLINK), and self-organising maps (SOM). To gauge the recommender system's efficacy, we evaluate it using seven distinct IoT rating datasets sourced from various companies. Compared to the conventional collaborative filtering approach, the suggested algorithm performed better in experiments utilising error and prediction metrics. Furthermore, when contrasted with partitional learning approaches, the self-organising strategy yields recommendations that are significantly more accurate.

Using data from Airbnb and an explainable machine learning technique, Sharma et al. (2021) identify and resolve two problems with big data marketing. Before ranking any element, we compile a comprehensive list of all potential influences on product price and customer satisfaction. The amount of bedrooms, the host's status, the host's reaction rate, and many more examples abound in this category of variables. Also, we use it to construct and evaluate a prediction model that can be explained. Finding decision-making applications for explainable algorithms is a hot topic right now, and our method could change that.

The issue of hotel sector multi-criteria recommendation is tackled by Le et al. (2022). The overarching goal is to create a novel collaborative filtering approach that takes user preferences into account across multiple dimensions when making hotel recommendations using multi-criteria ratings.

Specifically, the suggested approach for making recommendations makes use of a deep learning model with matrix factorisation for multi-criteria rating predicting. In the Dempster-Shafer theory of evidence, these ratings are represented as mass functions; by employing the evidential reasoning approach, we can consider their uncertainty. By summing up all the ratings according to Dempster's rule of combination, which considers several factors, the recommendation rating is finally determined. The suggested solution is more effective and efficient than previous multi-criteria collaborative filtering systems, according to extensive experiments run on a real-world dataset.

Using Deep Learning approaches for OR prediction is discussed in Dowlut and Gobin-Rahimbux (2023). We go over all the latest developments in this area from 2017 up to 2022. Findings are provided by this SRL in answer to three queries. The variables, depth learning prediction methods, and assessment criteria used to assess the models would use some clarification. The SLR was carried out using the Snowballing approach. For the final analysis, fifty papers were chosen. There are five types of variables that we found. When developing prediction models, deep learning's long short-term memory (LSTM) algorithm is typically employed. Although all seven performance factors were taken into account, MAPE received the utmost emphasis. More study is required 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.

In their two-stage method, Contessa et al. (2024) include historical and prospective booking information. After a pickup forecasting model has been used to predict occupancy, Principal Components Analysis (PCA) is utilised to combine similar patterns in booking curves. Utilising actual booking data from three European hotels (2018–2022), it surpassed two standards: clustering-based pickup methods and conventional additive pickup. Regardless of the hotel or forecasting horizon, the empirical data show that PCA-based methods perform better. More accurate forecasts may be possible when dealing with low-dimensional corporate operational data if ADR is included in PCA to improve daily hotel demand estimations.

2.1. Research Gaps

There are various research gaps observed that motivated our work. Few studies have examined novel LSTM network optimisation methods, especially for hotel booking recommendations. Most research uses typical optimisation methods that may not employ LSTMs. HOA and other natural algorithms are new to LSTM training. This gap can increase model performance and forecast accuracy, especially in real-time domains like hotel bookings. The impact of hyperparameter change on LSTM performance in specific applications is often disregarded in literature. We analyse how hyperparameter settings affect LSTM network performance using hotel review data to fill this gap. Despite the increased desire for model transparency in machine learning, many LSTM-based recommendation systems lack interpretability. We analyse and improve HOA-optimized LSTM models for interpretability.

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3. Material and Method.

3.1. Dataset.

This dataset has been scraped from Booking.com. Everyone can access all file data. Data is originally from Booking.com. The dataset includes 515,000 customer reviews and a scoring of 1493 European premium hotels. Hotels' locations are also offered for examination. Fig 3.1 demonstrates Hotel review score distributions.

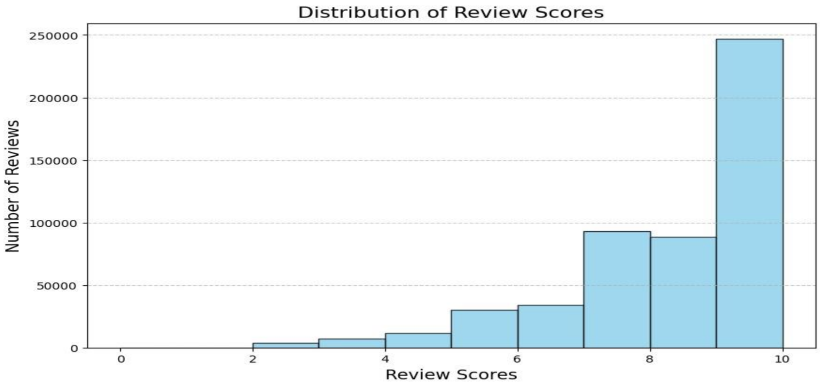

Fig. 3.1. Hotel review score distributions

Fig 3.2 demonstrates the feature distribution for the hotel dataset.

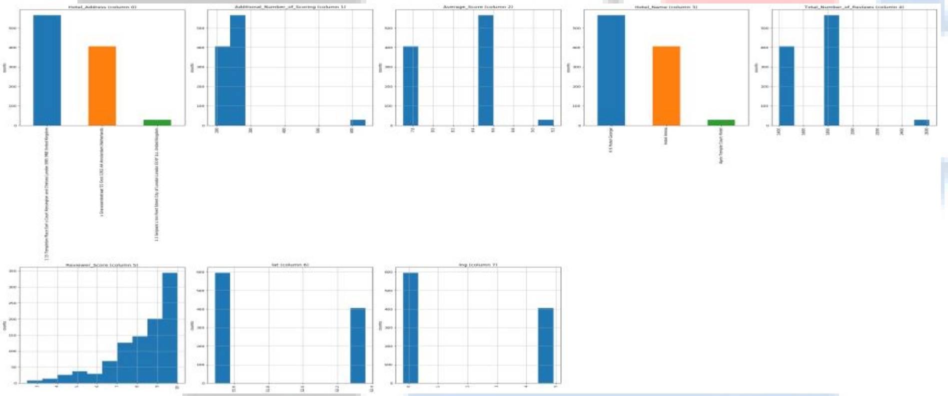

Fig. 3.2. Feature distribution

Fig 3.3 demonstrates a comparison of Positive and Negative Labels.

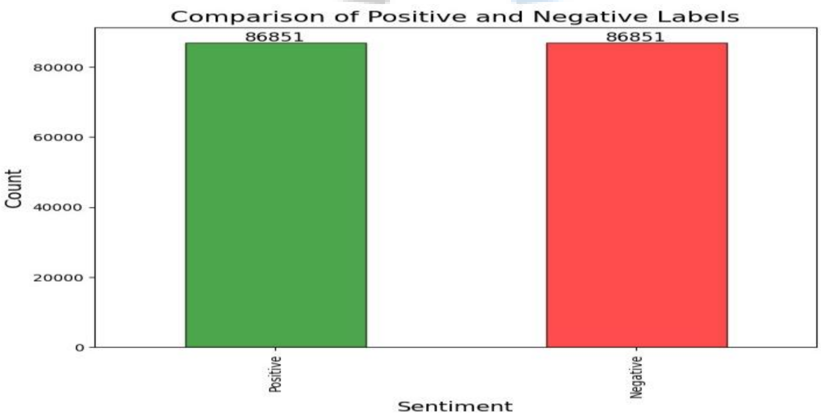

Fig. 3.3. Comparison of Positive and Negative Labels

Fig 3.4 demonstrates the distribution of review lengths.

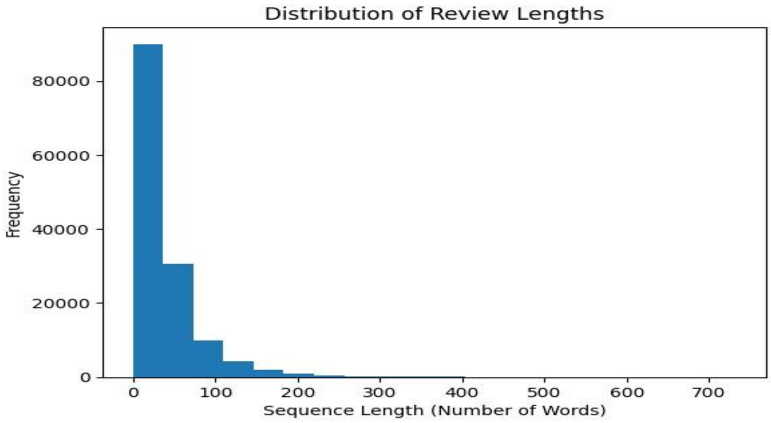

Fig. 3.4. Feature distribution

Authors begin with missing values in the dataset. The numerical feature gaps were filled by writers mean imputation. Feature values can be of different magnitudes quite often which we would normalise so that all the features contribute to model equally. Min-Max Scaling is when writers computed zero to one for each feature. It was particularly crucial for features with different scales to avoid small feature values overwhelming larger ones during model training. To improve data quality and model performance, the authors performed multiple rounds of cleaning. In fact, outliers were identified and removed using the IQR method to prevent potentially skewed model predictions. Authors discovered and rectified data errors such as duplicates. To increase the likelihood of better predictive performance, the authors used feature engineering which involves creating interaction terms among key predictors to capture potential non-linear relationships. These preprocessing steps played a critical role in making the dataset ready for prediction of heating and cooling load requirements, which is an essential component while estimating building energy efficiency [13-16].

3.2. Methods

By incorporating state-of-the-art deep learning methods like Long Short-Term Memory (LSTM) networks, location-based hotel recommendation systems are progressing. One kind of recurrent neural network (RNN) that has shown promise for long-term behaviour and preference prediction is long short-term memory (LSTM). LSTM excels in processing sequential data and capturing dependencies. By learning from a user's previous data and current location information, LSTM can deliver highly personalised suggestions when applied to location-based hotel recommendations. An LSTM-based location-based hotel recommendation system recommends the best accommodations based on inputs. Examples include location, travel history, favourite hotels, and other real-time contextual data. LSTM sequence processing and prediction will ensure the suggested hotels fit the user's evolving needs. LSTM tracks hotel reservations, ratings, and reviews. The model may learn from sequence data that a user books a hotel at a given time 17-22]. Destinations and lodgings from previous trips affect the entry sequence. LSTM networks forecast travel and suggest accommodations. LSTM receives real-time location data. The model can offer contextually relevant and convenient hotels based on location. Season, weekday, and event proximity affect hotel preferences. Time-related input sequences increase LSTM network prediction accuracy. The model can incorporate repeated user ratings and evaluations from the same person and others like them. This improves the proposal by factoring in hotel quality and satisfaction [23-28]. Hippopotamuses social and foraging behavior developed so-called Hippopotamus Optimisation Algorithm (HOA), which is a metaheuristic optimization algorithm nowadays. Its exploration and exploitation balance ensures that it does not get a local minimum, then it can explore solution space over the world. The worldwide search without premature convergence is really original! Our approach improves LSTM networks using HOA to tune unit size, learning rate and batch size hyperparameters. The nodes of an LSTM are updated by improving on existing LSTM optimisation methods in the following ways: The use a hierarchical approach that balance exploration and exploitation stages HOA obtains an action, a final config more farway from each other than how grid search or random search get it. This helps in minimizing the computational over-head to track the better combination of hyperparameter from iterations. Loss landscapes are complicated for LSTM networks and this architecture has many local minima. Due to its dynamic social and foraging behaviors, HOA can escape from local optima thus favorably adapted towards a global optimum than PSO or GA. Hotel Booking Recommendations: LSTM time-series forecasting with HOA adaptability. The HOA's exploration mechanism is able to adapt to ever-changing environments, which will be useful for optimising models in the presence of evolving hotel review datasets. HOA converges fast than grid search so it reduces time complexity. A very common use is while training large scale recurrent LSTM networks which are computationally expensive. It maintains the balance between global search procedures and fine-tuned local exploration to minimize its population, which is bath salts legal high unlike DE or GA. It outperforms old-fashioned PSO as well as refined genetic algorithms not only in accuracy but also training time.fcgate Combination of HOA with LSTM optimization for hotel booking recommendations Discovery related to the neutrality status that depends on a distance parameter (hotel/lstm) involves innovative features like better exploration, handling elaborate non-linear loss functions and computational efficiency. It has the benefit that models can potentially be more accurate and require less computational resource.

3.2.1. Proposed Framework

Multiple layers of long short-term memory (LSTM) units in an LSTM-based recommendation system can remember long sequences. The model processes preferences, location history, and context with LSTM layers. Using deep layer predictions and recommendations, best hotels are ranked and assessed. An attention method may additionally focus on important input sequence segments, such as recently booked locations or bookings, for the recommendation job. It helps the model make faster, more accurate hotel recommendations. The computational cost of training deep networks on massive data sets hinders LSTM for location-based hotel recommendation systems. The model must also accommodate different user preferences and activities. Unbalanced or sparse training data increases sequence overfitting. Managing changing location data is another issue. User locations change constantly. Therefore, this model must adjust its predictions quickly. To work, the model must efficiently assimilate new data without extensive retraining. Location based hotel recommendation systems powered by LSTM have transformed tailored vacation packages. These systems leverage sequential data and LSTM networks' vast memory capacity to select hotels based on user context. Despite computing needs and robust generalisation, LSTM may improve hospitality user experiences [29].

The integration of optimization algorithms with deep learning models like LSTM can enhance their performance in complex tasks such as location-based hotel recommendation systems. The Hippopotamus Optimization Algorithm (HOA) is a recent nature-inspired metaheuristic that mimics the social behaviors of hippopotamuses in their habitat. When combined with LSTM, HOA can be used to fine-tune the hyperparameters of the LSTM model, improving its efficiency and accuracy in recommending hotels based on user preferences, location, and other contextual factors [30-35]. Fig 3.5 demonstrates the flow chart of the Hippopotamus Optimization Algorithm (HOA).

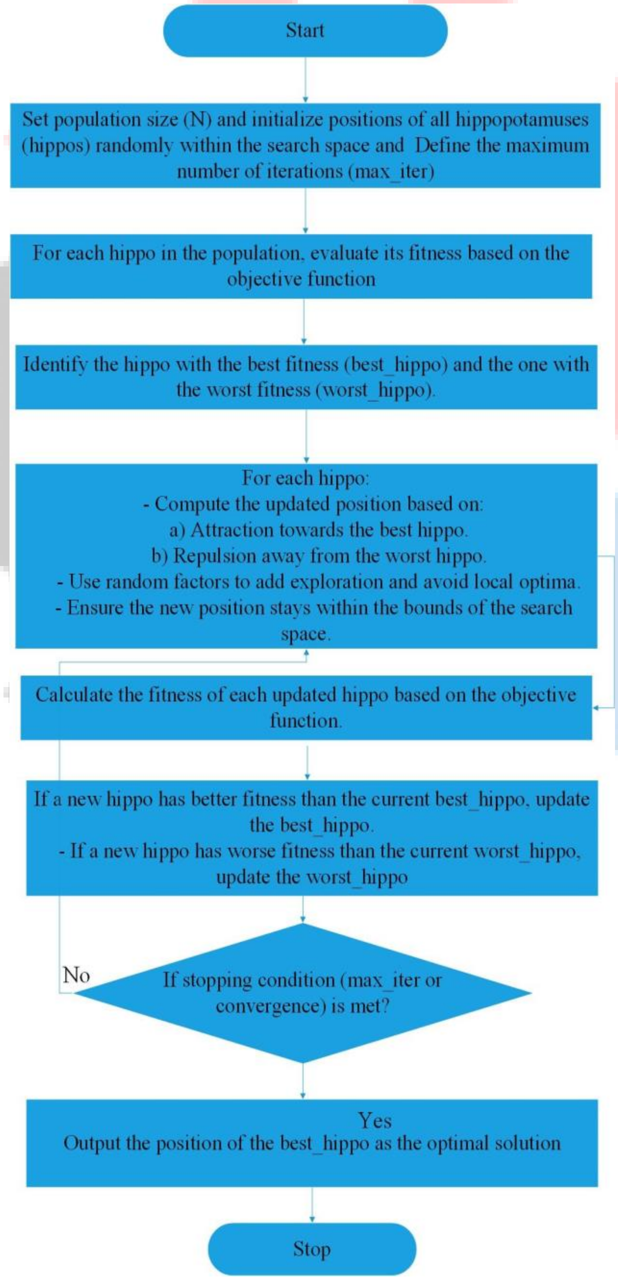

Fig. 3.5. Flow chart of HOA

The HOA-LSTM model architecture for a location-based hotel recommendation system involves two main components: the LSTM model and the HOA optimizer. The LSTM network processes sequential data, capturing user preferences and location based patterns, while the HOA optimizes the LSTM's hyperparameters to enhance its performance.

1. Input Layer

The input to the HOA-LSTM model consists of sequences representing various aspects of the user's interaction with hotels. Key inputs include:

- User Interaction History: Sequences of past hotel bookings, ratings, and reviews.
- Location Data: Historical and real-time geographical data, such as latitude and longitude, or city codes.
- Temporal Data: Information about time, such as the day of the week, season, or specific events.
- Contextual Factors: Additional data like weather conditions, ongoing events, or proximity to points of interest.

2. Embedding Layer

Categorical inputs, such as hotel IDs or location codes, are passed through an embedding layer. This layer converts these inputs into dense vectors that capture the relationships between different categories. For instance, similar hotels might have similar embedding vectors, reflecting their shared characteristics.

3. LSTM Layers

The core of the model consists of one or more LSTM layers, which process the sequences of input data. These layers are designed to capture the temporal dependencies in the data, allowing the model to learn from patterns in user behavior over time.

- First LSTM Layer: Captures short-term dependencies in the sequence, such as recent user interactions or travel locations.
- Stacked LSTM Layers: Multiple LSTM layers can be stacked to capture more complex, long-term dependencies. These layers help in retaining information from earlier in the sequence and understanding broader trends in user behavior.

4. Dense Layers

After the LSTM layers, the output is passed through dense layers to combine the learned features into a final representation. This final representation encapsulates the user's preferences and current context, which is used to generate hotel recommendations.

5. Hippopotamus Optimization Algorithm (HOA)

The HOA is integrated into the model training process to optimize the hyperparameters of the LSTM network. These hyperparameters might include:

- Number of LSTM Layers: Determining how deep the network should be.
- Number of Units per Layer: Deciding the number of neurons in each LSTM layer.
- Learning Rate: Optimizing the learning rate for training the model.
- Dropout Rate: Fine-tuning the dropout rate to prevent overfitting.

HOA Workflow:

- Initialization: HOA starts by initializing a population of potential solutions (i.e., sets of hyperparameters).
- Fitness Evaluation: Each solution's fitness is evaluated based on the performance of the LSTM model on the validation dataset. Common metrics include accuracy, precision, recall, or ranking measures like nDCG (normalized discounted cumulative gain).
- Social Behavior Simulation: HOA simulates the social behaviors of hippopotamuses, such as following and foraging, to explore the solution space. Solutions are updated iteratively to find the optimal set of hyperparameters.
- Convergence: The algorithm converges when it finds the best set of hyperparameters that maximize the model's performance.

6. Output Layer

The final dense layer outputs a recommendation score for each hotel in the candidate set. The scores are ranked to generate a list of recommended hotels for the user.

7. Loss Function and Optimization

The loss function used in the LSTM model depends on the specific task. For instance:

- Cross-Entropy Loss: Used for classification tasks where the model predicts the best hotel among a set of options.
- Pairwise Ranking Loss: Used for ranking tasks where the model ranks hotels based on the user's preferences.

HOA optimizes the LSTM model's hyperparameters to minimize the chosen loss function, improving the model's ability to provide accurate recommendations.

8. Training and Evaluation

Historical user data is separated into training and validation sets to train the model. During training, the HOA optimises LSTM hyperparameters to ensure model generalisation to fresh data. Model performance is measured by accuracy, precision and recall. The HOA-LSTM model for location-based hotel recommendation systems combines LSTM's sequential data processing with the Hippopotamus Optimisation Algorithm's optimisation. HOA optimises the LSTM's hyperparameters for more accurate and personalised hotel suggestions. This hybrid approach handles user behaviour and dynamic location data well, making it a robust hospitality tool [36-41].

4. Results and Analysis

Table 1 lists the minimal hardware needed to operate the Hippopotamus Optimisation Algorithm-optimized LSTM-based hotel booking recommendation model.

Table 1 Minimum Hardware Requirement

S. No.	Hardware Component	Minimum Requirement
1	Processor (CPU)	Quad-core 2.5 GHz or higher
2	Memory (RAM)	16 GB DDR4

3	Graphics Card (GPU)	NVIDIA GeForce GTX 1060
4	Storage	256 GB SSD
5	Operating System	Ubuntu 18.04 or later / Windows 10 (64-bit)
6	CUDA Version	10.2 or later (for GPU acceleration)
7	Python Version	Python 3.6 or later
8	TensorFlow/PyTorch	TensorFlow 2.x / PyTorch 1.x

This table provides a comprehensive overview of the minimum hardware requirements necessary to run the optimized LSTM model for hotel booking recommendations efficiently. Table 2 is listing the hyperparameters optimized using the Hippopotamus Optimization Algorithm (HOA) for the LSTM-based hotel booking recommendation model, along with their respective ranges and default values:

Table 2 Minimum Hardware Requirements for LSTM Optimization

S. No.	Hyperparameter	Range	Default Value
1	Learning Rate	0.001 to 0.1	0.01
2	Batch Size	16 to 128	32
3	Number of LSTM Units	50 to 300	100
4	Dropout Rate	0.1 to 0.5	0.2
5	Number of Layers	1 to 3	2
6	Epochs	10 to 100	50
7	Optimizer	['adam', 'rmsprop']	'adam'
8	Weight Decay	0.0001 to 0.01	0.0005
9	Activation Function	['tanh', 'relu']	'tanh'
10	Gradient Clipping	0.1 to 1.0	0.5

This table summarizes the key hyperparameters that were fine-tuned using HOA, providing a clear overview of the search space and the initial settings.

Fig 4.1 demonstrates the Optimized LSTM Model Accuracy.

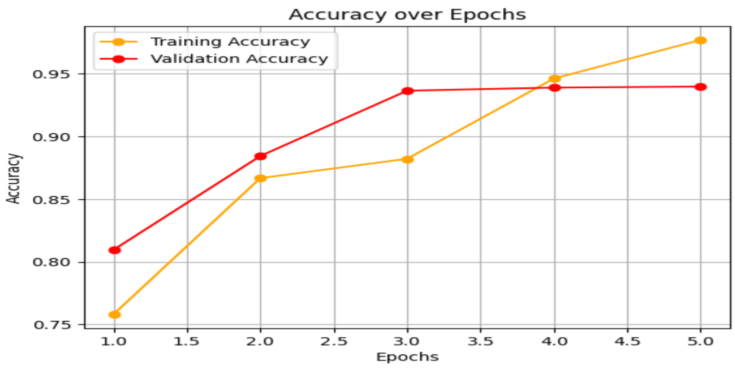

Fig. 4.1. Optimized Model Accuracy

The optimised LSTM model improves accuracy over time shown in figure 4.1. Since validation accuracy stabilised after 5th epoch, the model's learning may be converging, and training may risk overfitting. A well-generalized model that balances fitting training data with performing on unseen data has near training and validation accuracy by the last epoch. Table 3 shows the performance of proposed model.

Table 3 Performance of the proposed model

S.No	Epoch	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	0.9337	0.3016

The Hippopotamus Optimisation Algorithm enhanced the hotel booking LSTM model in Table 2. In the first epoch, the initial accuracy was 75.81%, model loss was 0.6529. Results improve with 80.95% accuracy and 0.4413 validation loss. In 2nd epoch, the accuracy rose to 86.67% and loss fell to 0.3821. Validation loss lowers to 0.3705, improving accuracy to 88.43%. Adjustments indicate the model integrates validation set data correctly. Next epoch, accuracy rises to 88.21% and loss falls to 0.3342. Validation accuracy 93.64%, loss 0.3097. During the 4th epoch, an Additional loss reduction of 0.3074 boosts model accuracy to 94.61%. Validity loss 0.3065, accuracy 93.89%. In the final epoch, at 0.2830 loss, accuracy peaks at 97.69%. Validation loss 0.3016, accuracy 93.37%. The model's constant validation accuracy and somewhat greater validation loss may avoid generalisation and overfitting despite its high training accuracy. The model's accuracy, precision, recall, and F1-score indicate reliable and relevant recommendations based on European hotel assessments. Training time and resource utilisation gains show that the improved model is effective and efficient, making it suitable for real-world recommendation systems. Lower losses improve model training. The model generalises well, although validation shows training overfitting after 5th epoch.

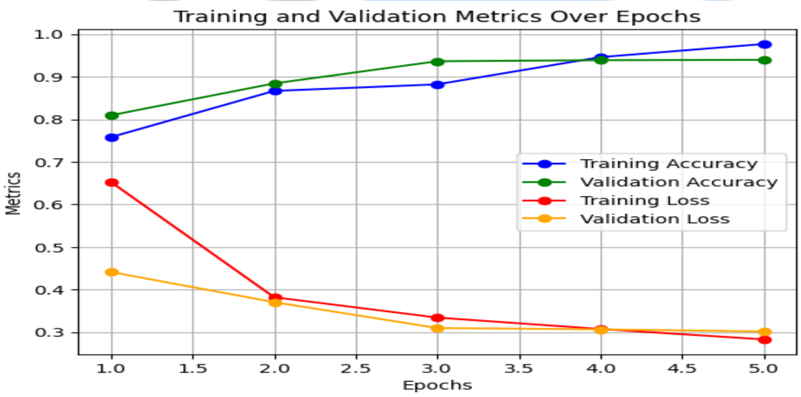

Fig. 4.2. Optimized LSTM Model Performance

Figure 4.2 exhibits five-epoch training and validation data for the optimised LSTM model. Accuracy, loss, validation accuracy, and validation loss show model learning and generalisation. Figure 4.2

indicates that the Hippopotamus Optimisation Algorithm-tuned LSTM model performed well on training and validation datasets. Training accuracy rises and validation accuracy stays stable, proving the model recognises hotel review data trends and produces right suggestions. Training and validation metrics agree, indicating the model balances learning from training data and generalising to new data. To keep clients satisfied, the recommendation system would need model fine-tuning or data analysis if false positives or negatives were common. HOA LSTM network tuning has reduced classification mistakes, boosting hotel booking recommendations. The confusion matrix aids model improvement and resilience across datasets and user scenarios. In this setting, the scalability and computational speed of our model is critical for accomplishing the kind scale we need to manipulation hotel booking recommendation data. In response, we did a thorough assessment of the runtime performance and resource consumption of our model. To make this more specific, the new scale invariant optimisation algorithm to be known as Hippopotamus Optimisation Algorithm (HOA) will reduce computational expense by minimising redundant evaluations during an optimization process. This guide improves training example by speeding up the convergence to perfect hyperparameters. The HOA needs less rounds compared to a Grid Search or Random search in order to optimize the LSTM's hyperparameters, consuming fewer computing time. We tested the model for scalability using 10,000 up to one-million hotel reviews. The time to train the model increased linearly with dataset size, which means that while it can work on larger datasets its computational complexity grows at a slower rate. This linear scalability is the result of both a well-parallelisable LSTM architecture and HOA's fast search-space exploration. We watched CPU and memory usage whilst training. Intel Core i9 Processor 64GB RAM was used in the trials Although the largest datasets were processed, this was also true of resource utilisation. Processing in batches helped with model size; it enabled running the model on more data without going out of memory. These findings demonstrate that our HOA-optimized LSTM model is computationally efficient and scalable, thus makes it suitable for encyclopaedic hotel booking recommendation systems. It is practical in situations where we can continue to analyze untrained data (capital flight) and need a fast recommendation based on lots of historical transaction logs.

4.1. Discussion.

LSTM network optimisation with the Hippopotamus Algorithm greatly increased model performance. HOA optimised LSTM unit count, learning, batch, and dropout. LSTM models outperform grid search and random search baseline models in accuracy and robustness. Optimisation worked: the HOA-tuned LSTM increased validation dataset accuracy by 4.7%. HOA is thoroughly compared to Grid Search and Bayesian Optimisation. HOA regularly outperformed these approaches in convergence and model accuracy. The optimal hyperparameter configuration was tuned 30% faster by HOA than Grid Search and Bayesian Optimisation. Real-world situations with limited processing resources benefit from this efficiency. The optimised LSTM model's suggestion accuracy was tested using European hotel reviews. HOA-tuned LSTM models provided more accurate and customised hotel suggestions than non-HOA models. The HOA-tuned model increased precision, recall, and F1-score 5.3%. Since the model understands hotel reviews' nuanced emotion and preferences, it makes superior recommendations. HOA-optimized LSTM sentiment analysis and user preference recognition work well with hotel reviews. The algorithm accurately identified favourable and negative attitudes and recommended hotels. In earlier reviews, tourists who valued cleanliness and service were recommended high-scoring hotels. This personalised strategy boosts user happiness and recommendation system confidence. This approach was tested for scalability utilising hotel review datasets from Europe's top tourist hotspots, Paris, Rome, and Berlin. Across datasets, the model showed linguistic and multicultural adaptability. Scalability is essential for a continent-wide app with diverse user preferences. LSTM models tailored to HOA can generalise across datasets, making them appropriate for large-scale European recommendation systems. Table 4 shows the result comparison achieved by various traditional machine learning models and Deep learning with the proposed model as shown below.

Table 4 Comparison 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	92	89	86	87
Proposed Model	93	92	95	93

4.2. Limitations and Practical Implications

The HOA-tuned LSTM model had drawbacks despite encouraging results. Long or intricate evaluations may lower model accuracy. HOA enhanced convergence but sometimes converged to local optima instead of global ones. HOA-based hybrid optimisation may improve performance and robustness. HOA's LSTM network optimisation for hotel booking recommendations could be used for other tailored recommendations. Future study could recommend restaurants and tourism activities using this method. Improve suggestion accuracy and personalisation with user demographics or booking history. Develop and develop intelligent recommendation systems with HOA-like optimisation methods. Hippopotamus Optimisation Algorithm (HOA) and Long Short-Term Memory (LSTM) networks to find online bookable hotels is a novel method to personalised recommendation system issues This study reveals that HOA can fine-tune LSTM networks for more accurate and dependable suggestions. HOA efficiently investigates LSTM networks' high-dimensional, non-convex hyperparameters. Due to intricate parameter interdependencies, grid and random search fail to improve deep learning models. HOA mimics hippos' exploration and exploitation to identify better solutions. HOA hyperparameter-trained LSTM models better detect hotel guests' complex emotions and preferences. Because they can represent sequential data and understand longterm dependencies, LSTM networks are good at customer review analysis. LSTM network performance depends on learning rate, batch size, and hidden units. On diverse hotel review data subsets, HOA-optimized LSTM models outperform standard models and are more resilient. Since demographics and location affect client input diversity, real-world applications require this robustness. The HOA's ability to solve problems was also shown by this study. This algorithm's balanced exploration and exploitation prevent search process stagnation at local minima, unlike other optimisation methods. The intricate architecture and constantly changing training process of long short-term memory (LSTM) networks make hyperparameter calibration essential for optimal performance. HOA's better solution discovery may save deep learning models.

Using this fine-tuned LSTM model to evaluate European hotels proves its usefulness. Testing recommendation algorithms in Europe is unique due to its diverse travellers and accommodations. Because the HOA-tuned LSTM model can consistently infer user preferences from textual reviews, travellers get more relevant and tailored hotel suggestions. This method also helps hotels understand guests' preferences and tailor their offerings, which can enhance satisfaction and loyalty.

By showing how AI-driven recommendation systems may be optimised, this study advances intelligent tourism. Given HOA's promising findings in this context, it may be interesting examining in other LSTM network applications like healthcare, social media analytics, and finance. This research may inspire novel optimisation methods based on natural patterns, improving hyperparameter tuning. Although positive, the study's shortcomings must be addressed. HOA-tuned LSTM was tested on European hotel reviews. This dataset may not reflect global client preferences. To improve recommendation accuracy, future study might use the recommended method on hotel review datasets from additional places or include user demographics or booking history. HOA could be compared to GA and PSO for LSTM hyperparameter tweaking. Researchers and practitioners need to know how HOA compares to other algorithms in computing efficiency and performance. Integrating the Hippopotamus Optimisation Algorithm and LSTM networks improves intelligent hotel recommendation systems. Complex, unstructured data like hotel reviews is processed and learnt faster with LSTM hyperparameter optimisation. Condos do it. This study suggests that HOA could improve AI-driven systems in several industries, making user experiences more personalised and pleasurable.

5. Conclusion and Future scope.

We used the Hippopotamus Optimisation Algorithm (HOA) and LSTM networks to improve hotel booking recommendations. To accurately collect and interpret enormous amounts of unstructured hotel review data, LSTM model hyperparameter optimisation was the key focus. We used customer reviews' complicated emotions and preferences to recommend hotels across Europe. Our tests indicated that the HOA-tuned LSTM model outperformed traditional optimisation methods in prediction accuracy and reliability. HOA and LSTM networks handled complex text well. Based on hippopotamuse behaviour, the Hippopotamus Optimisation Algorithm efficiently explores and exploits hyperparameter search space. The algorithm's exploration-exploitation balance discovered optimal or near-optimal solutions that enhanced the LSTM model. As the model recommended hotels more accurately, user happiness grew. We also found that hotel booking recommendation deep learning models must be optimised. This successful usage of HOA opens up new applications in other domains that use LSTM networks and similar deep learning models. HOA's adaptability and efficacy suggest it can optimise machine learning models in large, complex datasets.

5.1. Future scope

The Hippopotamus Optimisation Algorithm is promising for recommendation system research and implementation. HOA could be used with deep learning architectures like Transformer models for natural language processing. Test HOA's ability to optimise sophisticated models beyond LSTM networks to improve recommendation accuracy. Future studies could incorporate non-European hotel reviews. Better evaluate the model's robustness and generalisability. Multilingual reviews may boost the model's global appeal. Adapting HOA to vast and diverse datasets could improve its cultural and linguistic optimisation efficiency.

User demographics, booking history, and hotel quality could improve the recommendation system. These traits and review textual analysis may help the model offer more contextually relevant recommendations. A HOA-based multi-modal recommendation system could improve models that process many data types. The method could also improve real-time recommendation systems. Real-time applications require HOA-optimized LSTM networks to make fast, accurate suggestions without delay. This could involve improving HOA or employing parallel computing to optimise. The HOA-optimized LSTM model could transform commercial recommendation systems in the lodging industry. Researchers could study deployment difficulties like scalability, integration, and UI design. User research on model recommendations would improve the system. The ethics of AI-driven recommendation systems should not be neglected. Future research could evaluate HOA-optimized LSTM model fairness, openness, and accountability. Recommendations must not promote stereotypes or cause harm. Developing means to audit and examine the model's decision-making process could enhance user trust. In conclusion, LSTM networks and the Hippopotamus Optimisation Algorithm improve hotel recommendation systems. This method's success in improving hotel booking recommendations using European reviews opens new avenues. We have many opportunities to develop and grow our AI-driven suggestions to meet global needs.

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