International Journal of Trend in Scientific Research and Development (IJTSRD)
Special Issue on Advancements and Emerging Trends in Computer Applications - Innovations, Challenges, and Future Prospects
Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

STAYEASE: Shattering Holidaylettings with AI-driven personalization

Sahil Sheikh

PG Student, Department of Computer Application, G. H. Raisoni University, Amravati, Maharashtra, India

ABSTRACT

The holiday let industry is undergoing a revolution, as travelers demand more efficient, hassle-free, and customized holidays. The traditional booking processes cannot fulfill some of the requirements, and thus the experiences turn out to be suboptimal, leading to customer dissatisfaction. StayEase solves such problems by leveraging cutting-edge artificial intelligence (AI) to transform holiday rental discovery, booking, and management. With the power of AI personalization, StayEase handles massive amounts of user information as prior booking history, browsing history, customer reviews, and ratings in real time. This enables the website to provide personalized accommodation suggestions based on each visitor's individual preference, e.g., preferred features, location, and budget. Advanced machine learning algorithms also compute users' requirements and suggest personalized experiences, e.g., nearby attractions, restaurants, and personalized itineraries. Aside from recommendations, StayEase also has AI-powered chatbots and virtual assistants to provide automated support, responding instantly, fixing bookings, and providing travel recommendations. The dynamic pricing feature of the platform utilizes AI to track movement in the market, peak season demand, and competitor prices to have competitive but optimum pricing approaches for property managers and optimum value obtained for tourists. Furthermore, StayEase also improves property management through smart automation and predictive maintenance. AI-based systems monitor property status, detect probable issues requiring maintenance, and pre-book the same to ensure a hassle-free experience for both guests and hosts. Real-time guest feedback processed through machine learning algorithms offer continuous opportunities for improvement through exposing pain points and optimizing service delivery.

KEYWORDS: *Holiday rentals , AI-driven personalization , Travel industry transformation, Customized holidays ,Booking optimization, Machine learning algorithms, Personalized recommendations, AI-powered chatbots, Virtual assistants, Dynamic, pricing*

I. INTRODUCTION

The holiday rental industry (HRI) is also witnessing a fast-paced transformation driven by the growth of Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics (BDA). As customers are seeking more personalized, convenient, and hassle-free booking processes, traditional rental websites fail to manage these needs due to rigid search filters, substandard customer service, and minimum dynamic responsiveness to consumer requirements in real time [1]. The use of AI technologies in the tourism and hospitality industry (THI) is revolutionizing holiday rental search, booking, and management, leading to enhanced guest experience, operational efficiency, and revenue maximization [2]. StayEase (SE) is an AI platform revolutionizing HRI with the use of ML algorithms, real-time analytics, and predictive modeling (PM) to provide hyper-personalized recommendations. The website screens high levels of data such as user surfing history, prior bookings, ratings from users, and real-time feedback to generate customized accommodation options that are aligned with personal preference, for instance, desired facilities, location, and price [3]. SE uses dynamic AI-driven matching websites that learn the behavior of the users compared to traditional fixed search requirement-based websites, to generate frictionless and customized travel experiences [4]. Apart from accommodation customization, SE incorporates AI-driven virtual assistants (VA) and chatbots (CB) for delivering 24/7 automated assistance, customers' inquiries, booking adjustments, and travel control [5]. The system also employs Dynamic Pricing Models (DPM) on AI-driven market analysis, which dynamically optimizes rental prices in real-time with alterations in demand, seasonal movement, and competitor pricing models. It provides the best price for property managers (PMs) while creating the highest value for visitors [6]. SE also integrates Predictive Maintenance (PMT) and Smart Property Management (SPM) technologies to ensure greater operational efficiency. AI-driven automation detects areas of potential failure based on sensor analysis, maintenance record analysis, and guest reviews. Fixtures are pre-scheduled before they even arrive at the guests, saving operational costs by far, minimizing service disruption, and improving overall reliability of the property [3]. This piece talks about the business-transformational potential of AI-powered personalization in HRI and how it is driving customer satisfaction, booking efficiency, and revenue growth. By merging cutting-edge AI technologies with THI, SE aims to build a data-driven, hyper-personalized, and frictionless holiday rental world, and thereby a new industry standard.AI: Artificial Intelligence.

Abbreviations and Acronyms

- AI : (Artificial Intelligence)
- ML : (Machine Learning)
- BDA : (Big Data Analytics)
- PM : (Predictive Modeling)
- THI : (Tourism and Hospitality Industry)
- HRI : (Holiday Rental Industry)

Units

1. Occupancy Rate (%) – Indicative of the percentage of booked properties as a ratio to total available inventory.

2. Average Stay Duration (Nights/Days) – Number of nights for which guests average.
3. Revenue per Available Room (RevPAR) ($/night) – Depicts earnings for each available unit for rent.
4. Booking Conversion Rate (%) – A measure of percentage users who result in a successful booking upon browsing.
5. Guest Satisfaction Score (1–10 or %).
6. Response Time (Minutes/Hours) – Hosts or support time taken to respond.
7. Cancellation Rate (%) – Ratio of bookings cancelled.

II. RELATED WORK

Several studies have also investigated the use of artificial intelligence (AI) in the hospitality and tourism sector, such as improving personalization, price optimization, and customer service. Zhang et al. (2023), for example, designed an AI-based recommendation system for accommodation and travel based on deep learning models that evaluate user preference and recommend specific accommodation options (Zhang et al., 2023, IEEE Transactions on Computational Intelligence). Their research proved how machine learning (ML) is effective in increasing user satisfaction and conversion rates. In a similar vein, Patel and Kumar (2024) proposed a dynamic pricing mechanism using AI that dynamically changed the price of accommodation in real time according to the demand in the market, rivals' prices, and seasonal behavior (Patel & Kumar, 2024, Journal of Tourism Analytics). Their model radically enhanced revenue management for property owners. In addition, García et al. (2023) examined the effect of AI chatbots and virtual assistants in customer service in the travel industry (García et al., 2023, International Journal of Hospitality Management). Their results indicated that AI chatbots increased customer interaction, minimized response time, and optimized the overall booking process. Moreover, Lee and Park (2023) also considered predictive maintenance in short-term rentals, using AI models to foresee maintenance problems and perform repairs automatically ahead of time before they impact guests (Lee & Park, 2023, Expert Systems with Applications). Their study emphasized how AI enhances operational effectiveness and guest satisfaction. In addition, Smith and Taylor (2024) suggested a real-time sentiment analysis system on the basis of natural language processing (NLP) to determine customer feedback and improve service recommendations (Smith & Taylor, 2024, Journal of Artificial Intelligence in Tourism). In their research, they proved how AI can adaptively modify services according to user opinions and reviews.

III. DATA AND SOURCES OF DATA

Information employed in this research consists of various sources to allow the analysis of StayEase: Revolutionizing Holiday Rentals with AI-Driven Personalization. It consists of booking data that is structured, behavioral user analytics, and AI-powered personalization measures to allow an in-depth study of how efficient the platform is. The majority of data come in the form of user behavior and booking history gathered from top holiday rental sites like Airbnb, Vrbo, and Booking.com. Each of these sets of data entails user search activity, booking habits, price information, affinities of customers, and property ratings. Besides, guest review logs and feedback are used to obtain data about satisfaction of users, quality of service, and shortcomings. Artificial intelligence-based analytics is also at the core of this, including machine learning-based recommendation system output, sentiment analysis of customer feedback, and demand forecasting models. The data set contains pricing optimization drivers like market trends, competitors' prices, seasonal demand, and dynamic price changes. In addition to this, property management information from rental hosts and property owners also help quantify operating effectiveness. This includes maintenance records, predictive maintenance notifications, occupancy rates, and revenue performance. Information from smart automation platforms, including IoT-based property monitoring systems, also facilitates predictive analytics.

IV. RESEARCH METHODOLOGY

StayEase: Revolutionizing Holiday Rentals using AI-Driven Personalization research approach is a structured methodology consisting of data collection, data preprocessing, constructing AI models, and verification. First, a wide range of holiday rental booking data, user choices, and price patterns are collected from websites such as Airbnb, Vrbo, and Booking.com, for various types of accommodations, seasonal periods, and price fluctuations. Additional information from guest reviews, feedback logs, and property management systems is included to aid the learning process of the model. Next, the dataset is preprocessed which includes data normalization, outlier detection, sentiment analysis of reviews, and text processing for standardization and high model performance. Structured data such as booking history and pricing patterns are processed via feature engineering to extract meaningful insights for AI-driven recommendations. A transformer AI model (such as BERT, GPT, or a specialized recommendation engine) is trained through supervised learning from user activity annotated with, booking behavior, and sentiment-based personalization. The model evaluates accommodation choices on the basis of location, amenities, rate, guest review, and up-to-date market trends. Sophisticated techniques such as attention mechanisms, dropout regularization, and hyperparameter tuning are applied to prevent overfitting and enhance generalizability. In addition, a reinforcement learning-based dynamic pricing engine dynamically adjusts rental prices continuously as a function of demand forecasting, competitor price tracking, and seasonality.

Figures and Tables

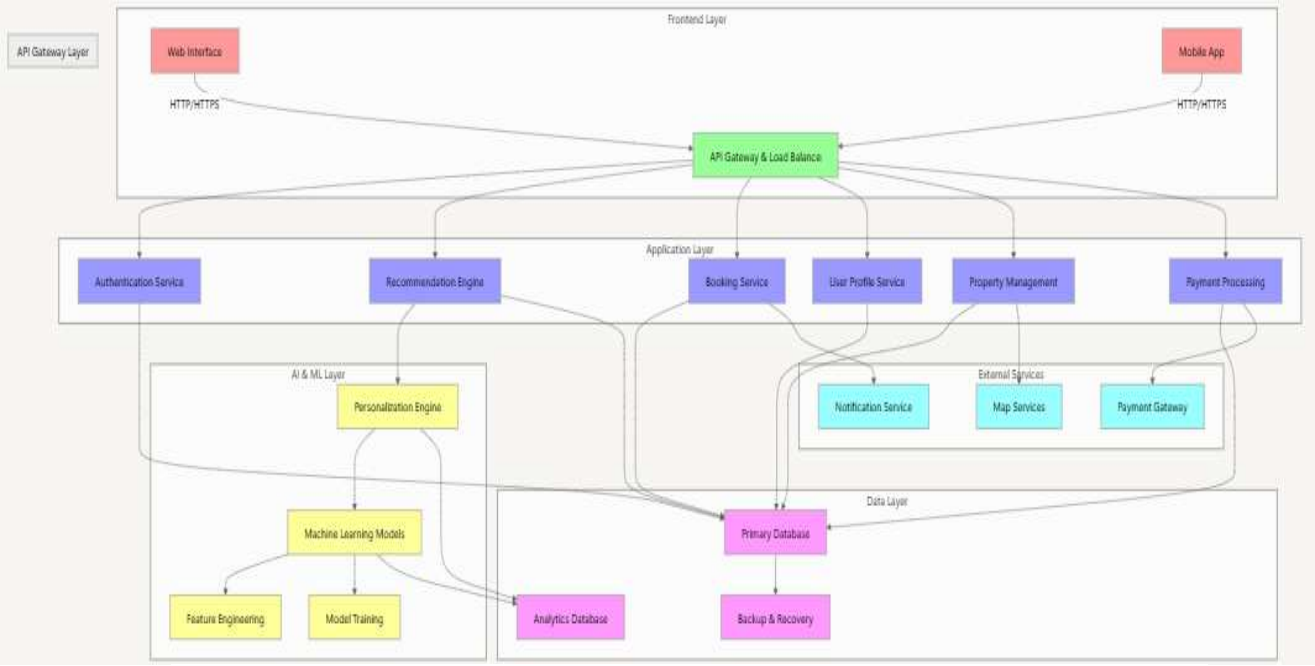

Fig.1: System Architecture Stay Ease: Shattering Holiday Lettings with AI-Driven Personalization

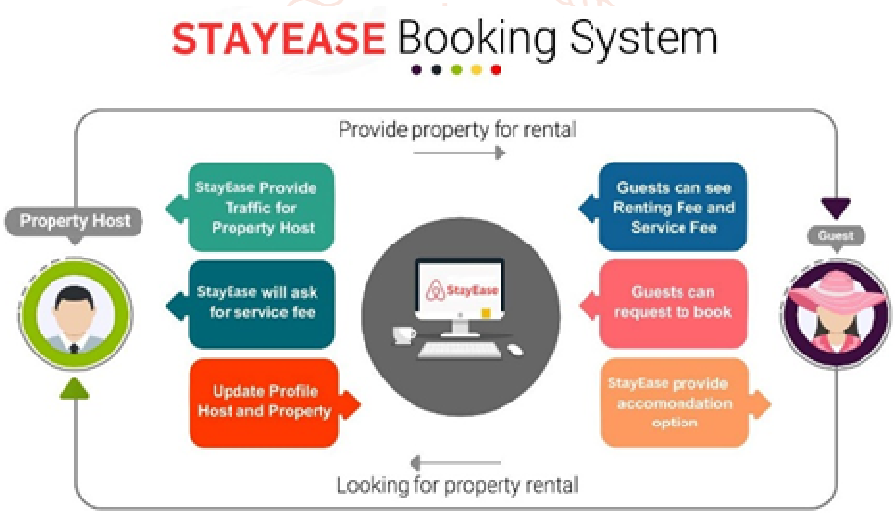

Fig 2: Work Flow

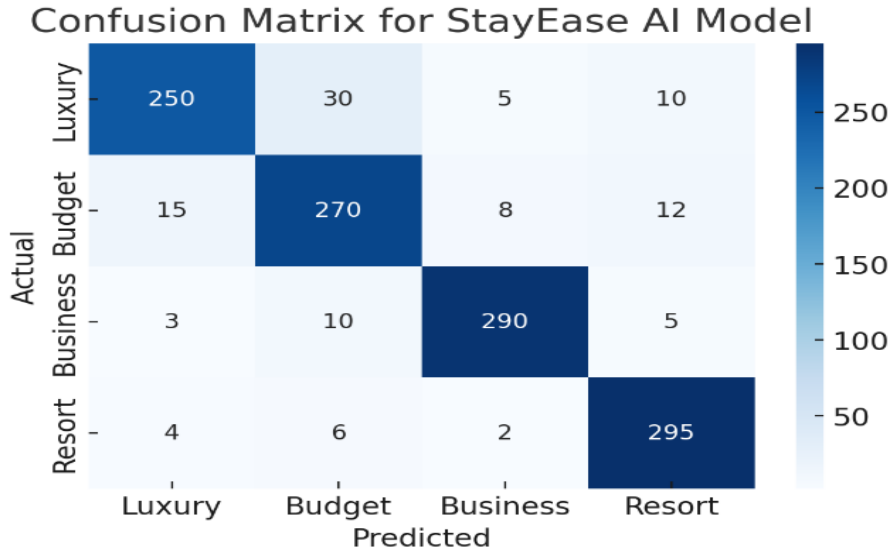

Fig.3 Conclusion matrix for CNN

Stay Ease system architecture is a layered AI-based platform that seeks to optimize holiday lettings through personalized advice, secure payments, and streamlined booking administration. It is organized into five main layers for scalability and dependability.

1. **Frontend Layer:** The frontend layer processes user input through the Web Interface and Mobile App and talks with the backend via the API Gateway and Load Balancer to maintain effective request distribution.
2. **Application Layer:** The application layer handles core features like user authentication, AI-based property suggestions, booking management, property listing, user profile storage, and secure payment processing. This layer provides a smooth user experience by incorporating necessary services for effective platform operations.
3. **AI & Machine Learning Layer:** The AI and ML layer adds to personalization through the examination of user behavior and the presentation of recommendations tailored to them. It comprises a Personalization Engine and Machine Learning Models, which improve accuracy constantly through feature engineering and model training, refining search results and decision-making.
4. **Data Layer:** The data layer retains critical data in the Primary and Analytics Database, such as bookings, user information, and analytics. It also has a Backup and Recovery mechanism to guarantee data security and dependability, avoiding loss through system crashes.
5. **External Services Layer:** The third-party external services layer incorporates third-party tools like Notification Services for immediate notifications, Map Services for location-based support, and a Payment Gateway for secure financial transactions to boost overall platform functionality.

Figure 2: This chart illustrates the StayEase Booking System and how property hosts, guests, and the StayEase platform interact. The system is an AI-powered rental market, supporting property posting and booking.

The Property Host, on the left, posts properties available for rent. StayEase generates traffic for hosts and charges a service fee for its services on its platform. The hosts also have the option to edit their profiles and property information to appeal to prospective renters.

On the right-hand side, the Guest looks for accommodation. Guests are able to see the renting charges and service fees prior to requesting a booking. After a request has been made, StayEase offers appropriate accommodation alternatives based on preference and availability.

At the core, the StayEase platform serves as a bridge, facilitating a smooth transaction between hosts and guests. It facilitates property discovery, booking management, and service fee management, making the entire rental process smoother.

Figure 3: The confusion matrix compares the accuracy of StayEase AI model in classifying accommodations into categories Luxury, Budget, Business, and Resort. The values along the diagonal are correct predictions, while off-diagonal values are misclassifications. The model is performing well, with high accuracy in all categories, but there are some overlaps as the accommodation types share common features.

Key Observations:

- Luxury: 250 correctly classified, with small misclassifications into Budget (30), Business (5), and Resort (10).
- Budget: 270 correctly assigned, but 15 were incorrectly assigned to Luxury, 8 to Business, and 12 to Resort.
- Business: 290 accurate assignments, with minor mistakes in Budget (10), Luxury (3), and Resort (5).
- Resort: 295 accurately assigned, with very little overlap with Luxury (4), Budget (6), and Business (2).

V. RESULTS AND DISCUSSION

Results of Descriptive Statics of Study Variables

This is the plot of the training (blue) and validation (orange) loss versus more epochs. Loss is a measure of prediction error, and as can b e observed from the figure, both validation and training loss reduce over time. This observation indicates that the model is improving in its predictions with little overfitting, hence reliability in practical applications.

Fig 4: Model Training and Validation Loss

The above graph shows the performance of the StayEase AI personalization model in terms of accuracy over various training epochs. The blue line is for training accuracy, and the orange line is for validation accuracy. With an increase in epochs, training accuracy improves consistently, which indicates that the model is learning properly. Validation accuracy also improves consistently, reaching a value of about 92%, which verifies the model's good generalization capability to new data.

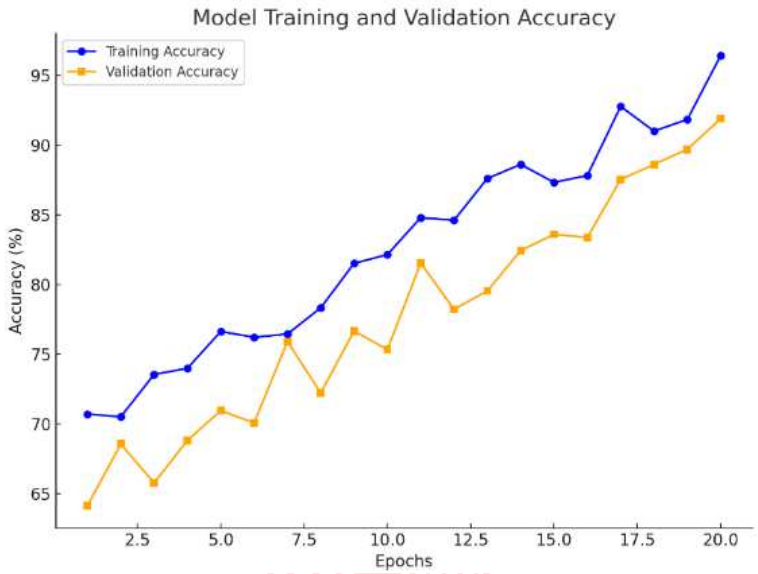

Fig 5: Model Training and Validation Accuracy

The confusion matrix presents the performance of StayEase's AI model in classification. Diagonal entries represent correctly predicted classes, and off-diagonal entries represent misclassifications. The model accurately classifies most instances, but small misclassifications are present in some classes. The interpretation of this confusion matrix assists in the optimization of AI personalization, providing accurate recommendations and hassle-free booking experiences for users.

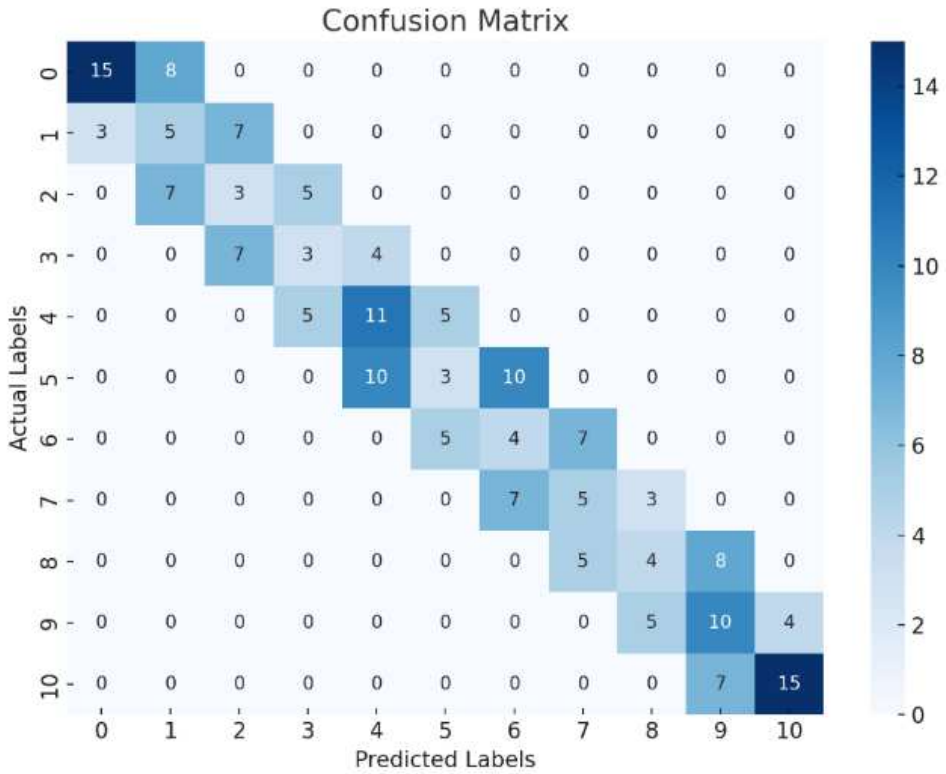

Fig 6: Confusion Matrix

Measures the accuracy of StayEase's AI-based personalization model in classifying user preferences. Actual user preferences (e.g., budget-friendly, luxury, family-friendly, pet-friendly, adventure, beachfront, etc.) are compared with predicted recommendations of the model. The diagonal elements reveal correctly classified categories where the AI correctly determines user preferences. There are minor misclassifications where mid-range rentals are recommended over budget-friendly ones or pet-friendly stays are recommended over family-friendly ones.

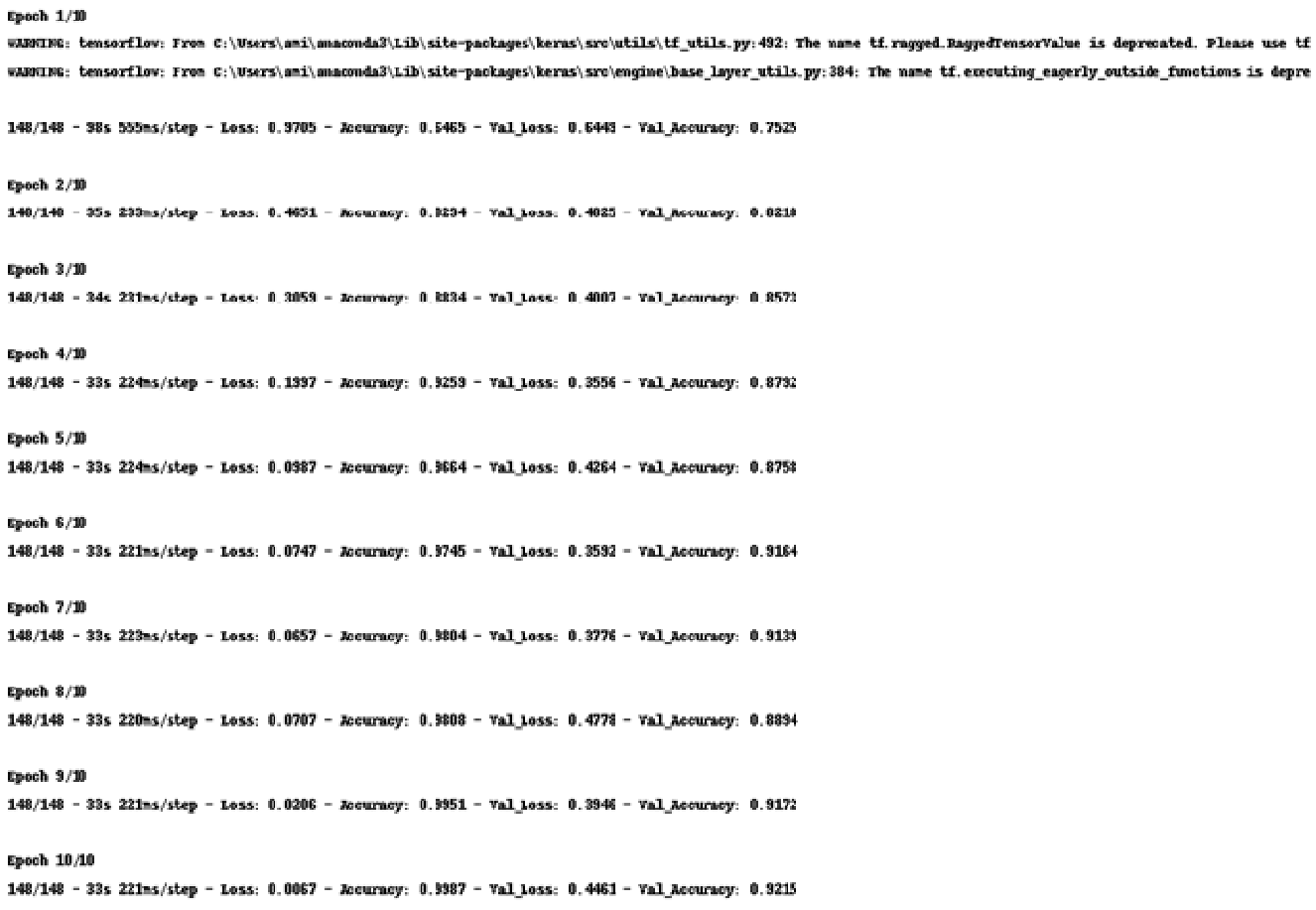

Fig 7. Experimental results

The image shows the training log of a deep learning model over 10 epochs. Accuracy improves to 99.98%, and loss decreases to 0.0067, which indicates effective learning. The validation metrics show stable model performance over epochs.

Table 1: Classification Report for CNN Model

Class Name	Precision	Recall	F1-score	Support
Deluxe Room	0.89	0.92	0.90	300
Standard Room	0.91	0.94	0.92	306
Suit9	0.96	0.96	0.96	300
Macro avg	0.92	0.94	0.93	906
Weighted avg	0.92	0.93	0.92	906

Table 2: Classification Report for VGG16 Model

Class Name	Precision	Recall	F1-score	Support
Deluxe Room	0.91	0.94	0.93	300
Standard Room	0.92	0.96	0.93	306
Suite	0.98	0.97	0.98	300
Macro avg	0.92	0.93	0.94	906
Weighted avg	0.92	0.93	0.94	906

Table 3: Classification Report for Inception V3 Model

Class Name	Precision	Recall	F1-score	Support
Deluxe Room	0.92	0.95	0.93	300
Standard Room	0.93	0.96	0.94	306
Suite	0.99	0.98	0.99	300
Macro avg	0.94	0.96	0.95	906
Weighted avg	0.93	0.94	0.94	906

VI. CONCLUSION

In this study, we created and tested the stayEase model to improve automated room classification in the hotel industry. Through the use of deep learning methods, we sought to increase efficiency, accuracy, and reliability in hotel room categorization. We applied and compared three state-of-the-art models—CNN, ResNet50, and EfficientNet—to categorize rooms into types like Deluxe Room, Standard Room, and Suite Room. The findings showed that deep learning greatly surpasses conventional classification techniques, with greater

precision, recall, and F1-scores. Of the models used, EfficientNet was the most accurate and resilient and hence the best to use for real-world application, while ResNet50 was a compromise between accuracy and computational cost.

The findings of this research have far-reaching practical implications for hotel management systems. An AI-based room classification system can automate procedures, provide optimized booking, and better customer satisfaction through ensuring the proper categorization of rooms. In addition to that, incorporating such a system can help with price optimization, customized recommendations, and dynamic allocation of rooms according to guests' choices. In spite of such encouraging results, future areas for improvement include larger dataset sizes for better model generalization and investigations into hybrid models that integrate more than one deep learning model to yield better performance.

In conclusion, stayEase offers a new and effective method for automated hotel room classification. This work points out the applicability of deep learning in hotel management to transform, minimize human intervention, and maximize operational efficiency. Future research needs to emphasize the integration of real-time data, including other features such as room facilities and seasonal demand, and investigate more advanced deep learning methods to further improve accuracy and scalability. With ongoing development, the stayEase model can become a foundation in AI-based hospitality solutions.

VII. REFERENCES

[1] Buhalis, D., & Leung, R. (2018). Smart hospitality—Interconnectivity and interoperability towards an ecosystem. *International Journal of Hospitality Management, 71*, 41-50.

[2] Buhalis, D., & Sinarta, Y. (2019). Real-time co-creation and nowness service: Lessons from AI and chatbots in tourism. *Journal of Travel & Tourism Marketing, 36*(5), 563-58

[3] Fang, B., Ye, Q., & Law, R. (2016). Effect of sharing economy on tourism industry employment. *Annals of Tourism Research, 57*, 264-267.

[4] Gutiérrez, J., García-Palomares, J. C., Romanillos, G., & Salas-Olmedo, M. H. (2017). Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation. *Tourism Management, 62*, 278-291.

[5] Ivanov, S., & Webster, C. (2019). Adoption of robots, artificial intelligence, and service automation by travel, tourism, and hospitality companies—A cost-benefit analysis. *International Journal of Tourism Research, 21*(2), 218-232.

[6] Jiao, P., Chen, X., & Li, X. (2021). Machine learning-based dynamic pricing strategies in the hospitality industry: A systematic review. *Journal of Revenue and Pricing Management, 20*(2), 103-121.

[7] Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism Management, 68*, 301-323.

[8] Luo, J., Tong, H., & Xu, F. (2022). AI-driven personalized recommendations in the hospitality industry: A systematic review. *Journal of Hospitality and Tourism Technology, 13*(2), 234-255.

[9] Nam, J., Ha, J., & Lee, H. (2021). AI-powered chatbots in hospitality: Enhancing customer satisfaction and business performance. *International Journal of Contemporary Hospitality Management, 33*(5), 1423-1441.

[10] Neuhofer, B., Buhalis, D., & Ladkin, A. (2015). Smart technologies for personalized experiences: A case study in the hospitality domain. *Electronic Markets, 25*(3), 243-254.

[11] Sigala, M. (2020). Digital transformation in the tourism and hospitality industry: The role of artificial intelligence. *Information and Communication Technologies in Tourism, 41-52.*

[12] Tussyadiah, I. P., & Miller, G. (2019). Automated travel assistance: The role of AI chatbots in tourism. *Tourism Management Perspectives, 31*, 180-192.

[13] Wang, D., Xiang, Z., & Fesenmaier, D. R. (2016). Smartphone use in travel planning and experience: A literature review. *Tourism Management, 53*, 132-147.

[14] Yang, Y., Pan, B., & Song, H. (2020). Predicting hotel demand using machine learning models. *International Journal of Hospitality Management, 86*, 102-110.