# Evaluating the Performance of AlexNet and SVM for Tourism Recommendation

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Abstract: This study aimed to enhance a tourism recommendation system using the novel AlexNet classifier, contrasting it with the Support Vector Machine (SVM) algorithm. An alpha value of 0.05 and G Power of 0.8 determined an appropriate sample size, with a confidence interval of 95%. Of the 5,456 samples, 3,819 were for training and 1,637 for testing. The AlexNet and SVM algorithms were labelled as "Group 1" and "Group 2", respectively, and both underwent 20 test iterations. Results revealed the AlexNet Classifier achieved a 97.20% accuracy rate, surpassing the SVM's 92.45%. A significant statistical difference was confirmed between the two algorithms, suggesting AlexNet provides more accurate travel recommendations.

## 1 INTRODUCTION

The purpose of these systems is to assist travellers in discovering new tourist destinations and experiences that suit their interests and budget and to provide personalised recommendations for planning trips (Duen-Yian Yeh, 2015). This technology is a valuable resource for travellers and travel-related businesses, facilitating the discovery and planning of travel experiences and enhancing trip enjoyment using the innovative categorisation technique. Tourism recommendation systems are employed in various contexts to help travellers discover and plan their trips. Online travel agencies such as Expedia and Booking.com might use these systems to recommend places and activities based on prior reservations and interests (Kevin Meehan, 2013) (Palanivelu, J. et al. 2022). Travel agencies can harness recommendation system technology to plan tailored holidays and business trips. Simultaneously, tourism boards and destination marketing organisations might promote local attractions and activities using the innovative categorisation technique (Aiden McCaughey, 2014). Airlines might also adopt recommendation systems to suggest tourist destinations and activities based on past bookings and preferences, offering additional travel-related products and services like car hires and hotel reservations. By using the creative categorisation technique, tourism recommendation systems can be beneficial for various travel-related businesses and organisations, attracting and retaining customers with relevant, personalised recommendations (Ricardo Colomo-Palacios, 2017).

Over the past five years, nearly 175 articles on tourism recommendation systems have been published in sources such as IEEE Xplore, Google Scholar, and Springer. These systems let users enter a photo or a keyword detailing their desired visit type and then scour a database for tourist destinations that match the visual traits or keywords provided (Liangliang Cao, 2010) (Karthik B et al. 2022). The system categorises a vast set of geotagged web photos by location, picking out representative images for each group, subsequently offering these as recommendations to users (Andrew Gallagher, 2021). As smartphone manufacturers integrate more sensors, developers can discern a user's context with increased accuracy, pivoting to a multifaceted contextual approach rather than a sole reliance on location (Damianos Gavalas, 2014). A comprehensive review of smart e-Tourism recommendation systems featured in Artificial Intelligence journals and conferences since 2008 has been undertaken.

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The literature review on tourism recommendation systems presents several gaps. A notable absence is research investigating personalisation's influence on system efficacy. Although numerous tourism recommendation systems profess to furnish personalised advice, scant research delves into how adeptly these systems grasp individual proclivities or the consequential effect on recommendation quality. In this project, an innovative categorisation method classifies tourist sites based on location specialities and user interests, bolstering accuracy. Thus, this research's paramount objective is to heighten the accuracy of the tourism recommendation system, favouring the novel AlexNet classifier over the Support Vector Machine algorithm.

# 2 MATERIALS AND METHODS

The purpose of these systems is to assist travellers in discovering new tourist destinations and experiences that suit their interests and budget and to provide personalised recommendations for planning trips (Duen-Yian Yeh, 2015). This technology is a valuable resource for travellers and travel-related businesses, facilitating the discovery and planning of travel experiences and enhancing trip enjoyment using the innovative categorisation technique. Tourism recommendation systems are employed in various contexts to help travellers discover and plan their trips. Online travel agencies such as Expedia and Booking.com might use these systems to recommend places and activities based on prior reservations and interests (Kevin Meehan, 2013) (Palanivelu, J. et al. 2022). Travel agencies can harness recommendation system technology to plan tailored holidays and business trips. Simultaneously, tourism boards and destination marketing organisations might promote local attractions and activities using the innovative categorisation technique (Aiden McCaughey, 2014). Airlines might also adopt recommendation systems to suggest tourist destinations and activities based on past bookings and preferences, offering additional travel-related products and services like car hires and hotel reservations. By using the creative categorisation technique, tourism recommendation systems can be beneficial for various travel-related businesses and organisations, attracting and retaining customers with relevant, personalised recommendations (Ricardo Colomo-Palacios, 2017).

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## 2.1 AlexNet Classifier

AlexNet is a classifier that utilises a deep neural network architecture to identify patterns and features in input data, predicting the class to which it belongs (Priyadarshiny Dhar, 2021). What distinguished AlexNet was the employment of the ReLU activation function coupled with dropout regularisation technology. These advancements substantially enhanced the model's capability to generalise to new data and curtailed overfitting. It has mastered the recognition of an extensive array of image features and can classify new images based on these learned attributes.

Pseudo code
Input: An image of size 227 x 227 x 3
Output: The predicted class label

# Define the AlexNet architecture

1. Convolution layer 1 with 96 filters of size 11x11, stride 4, and padding 0, with ReLU activation

2. Max pooling layer with kernel size 3x3 and stride 2
3. Fully connected layer with 4096 neurons and ReLU activation
4. Dropout layer with a probability of 0.5
5. Fully connected layer with 4096 neurons and ReLU activation
6. Dropout layer with a probability of 0.5
7. Output layer with 1000 neurons (corresponding to the 1000 ImageNet classes) and softmax activation

# Preprocess the input image
1. Subtract the mean RGB values of the training set from the input image
2. Scale the pixel values to [0, 1]

# Forward pass through the network
1. Pass the preprocessed input image through the convolutional layers, pooling layers, and fully connected layers
2. Compute the softmax probabilities for each class using the output layer

# Return the predicted class label
1. Retrieve the class identifier associated with the maximum softmax probability

## 2.2 Support Vector Machine (SVM) Algorithm

Support Vector Machine (SVM) is a popular supervised learning algorithm used for classification and regression tasks. It is especially effective for classification problems. The objective of the SVM algorithm is to create the optimal decision boundary, termed a hyperplane, that can divide an n-dimensional space into classes to classify new data points accurately (David L. Olson, Dursun Delen, 2017). The SVM algorithm selects the extreme points, termed support vectors, that assist in creating the hyperplane. These support vectors lend the algorithm its name: Support Vector Machine.

The testing was conducted using a Jupyter Notebook on a hardware device equipped with an AMD Ryzen 5 3500U processor, 8GB of RAM, a 1TB HDD, and a 256GB SSD, running the Windows 11 operating system. Both the Chrome browser and SPSS software were utilised for statistical analysis.

## 2.3 Testing Procedure

To perform semi-supervised clustering on a dataset using the Anaconda Navigator and Jupyter Notebook, follow these steps:

1. Install the Anaconda Navigator and launch it.
2. Open a Jupyter Notebook by entering the command "jupyter notebook" in the terminal.
3. Create a new notebook by clicking the "New" button in the top right corner.
4. In the notebook's first cell, install and import the necessary libraries: pandas, numpy, matplotlib, seaborn, sklearn, tensorflow, and jupyter themes.
5. Load the dataset – a CSV file from Github with 5456 records – which will be split for training and testing in a 70:30 ratio.
6. Divide the dataset into separate sets for testing and training.
7. Input the Python code to execute semi-supervised clustering in a cell.
8. Execute the code by clicking the "Run" button.
9. Note the model's accuracy in an Excel sheet and further analyse it using SPSS software.

## 2.4 Statistical Analysis

In this research study, IBM SPSS Version 26 is used for an exhaustive statistical analysis of multiple variables. The main aim is to assess the mean accuracy using the Independent Sample T-Test. The study also employs bivariate correlation analysis in SPSS to produce a detailed correlation table (Okagbue 2021). The independent variables examined are "places" and "reviews", with "accuracy" being the dependent variable.

The analysis considers independent variables such as accuracy, standard mean error, and standard deviation (Okagbue 2021). An Independent Sample T-Test is carried out on these variables to scrutinise the outcomes. The dependent variables in focus are the AlexNet Classifier and the SVM algorithm.

# 3 RESULTS

Tourist destinations can be more effectively recommended using these systems. The independent sample T-test compared the accuracy between the AlexNet Classifier and SVM algorithms. The results demonstrated that the AlexNet Classifier achieved a higher accuracy rate of 97.20% compared to the SVM algorithm's 92.45%. The p-value of 0.000 from the independent sample T-test signifies a statistically significant difference between the two algorithms.

Table 1 displays the mean accuracy, standard deviation, and standard error mean for both the AlexNet Classifier and the Support Vector Machine algorithm. The AlexNet Classifier's average accuracy is 97.20%, while the Support Vector Machine algorithm records a mean accuracy of 92.45%. Table 2 offers a comparative review of raw data values for both algorithms. This analysis uses a dataset of 40 samples, split evenly with 20 samples for each algorithm. Table 3 presents the independent sample T-Test results for the AlexNet Classifier and Support Vector Machine algorithm, detailing the significance and standard error. The study assumed equal variances of 4.531.

Figure 1 showcases the comparative mean accuracy between the AlexNet Classifier and the SVM algorithm. It's evident from the figure that the AlexNet Classifier, with a mean accuracy of 97.20%, outperforms the Support Vector Machine algorithm, which has a mean accuracy of 92.45%.

Table 1: The SVM algorithm's mean accuracy is 92.4585, compared to 97.2080 for the AlexNet Classifier. Additionally, the following table reveals that the AlexNet standard deviation is 2.10600 and the standard error mean is 0.47092.

| Group Statistics | Algorithm | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Accuracy | AlexNet | 20 | 97.2080 | 2.10600 | 0.47092 |
| | SVM | 20 | 92.4585 | 4.18753 | 0.93636 |

Table 2: Accuracy of AlexNet and SVM of 20 samples each. AlexNet Classifier has given the highest accuracy of 99.20 and the SVM algorithm has given the accuracy of 98.89.

| SAMPLES | GROUP 1Accuracy in % (AlexNet) | GROUP 2 Accuracy in % (SVM) |
|---|---|---|
| TEST 1 | 98.05 | 82.78 |
| TEST 2 | 97.65 | 88.62 |
| TEST 3 | 97.02 | 88.74 |
| TEST 4 | 99.86 | 89.98 |
| TEST 5 | 96.12 | 88.56 |
| TEST 6 | 96.45 | 87.28 |
| TEST 7 | 98.66 | 89.99 |
| TEST 8 | 97.55 | 90.12 |
| TEST 9 | 98.87 | 98.89 |
| TEST 10 | 98.45 | 92.56 |
| TEST 11 | 98.22 | 95.63 |
| TEST 12 | 96.67 | 96.12 |
| TEST 13 | 96.45 | 95.41 |
| TEST 14 | 97.52 | 96.09 |
| TEST 15 | 98.75 | 94.51 |
| TEST 16 | 91.20 | 98.80 |
| TEST 17 | 92.80 | 95.66 |
| TEST 18 | 98.77 | 93.62 |
| TEST 19 | 95.90 | 98.06 |
| TEST 20 | 99.20 | 97.40 |

Table 3: An independent sample T-Test analysis of the AlexNet Classifier and Support Vector Machine algorithm, with the significance value of 0.000 and standard error of 1.04811.

| Independent samples test | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig | t | df | Sig(2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference: Lower | 95% Confidence Interval of the Difference: Upper |
| accuracy | Equal variances assumed | 10.425 | 0.003 | 4.531 | 38 | 0.000 | 4.74950 | 1.04811 | 2.62771 | 6.87129 |
| | Equal variances not assumed | | | 4.531 | 28.033 | 0.000 | 4.74950 | 1.04811 | 2.60266 | 6.89634 |

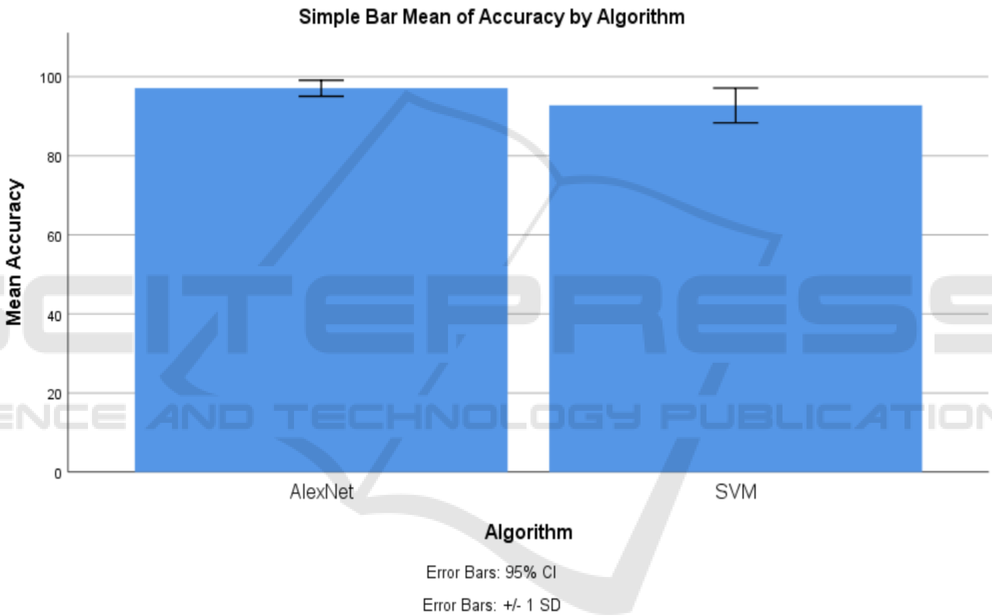


Figure 1: Analysis of the AlexNet and SVM Classifier. The AlexNet and SVM have respective mean accuracy of 97.20% and 92.45%. X axis: Alex Net Classifier vs SVM Classifier, Y axis: Mean Accuracy +/- 1 SD.

## 4 DISCUSSION

The AlexNet Classifier algorithm demonstrated superior accuracy for tourism recommendations, recording an accuracy rate of 97.20% compared to the SVM algorithm's 92.45%. Statistically, the findings were significant, evidenced by a p-value of 0.000. This signals a notable difference between the two algorithms' performance. The adoption of the AlexNet Classifier markedly elevated the SVM algorithm's accuracy, as highlighted by a p-value below 0.05.

The majority of researchers and industry experts concur that tourism recommendation systems offer invaluable support to travellers in uncovering new tourist destinations and experiences using innovative categorisation techniques. These systems expedite the recommendation process, aligning tourists with destinations and activities tailored to their interests and budgets. They are particularly beneficial for travellers pressed for time or those seeking bespoke travel experiences (Eleonora Pantano, 2019). The systems also generate personalised recommendations rooted in travellers' past activities and inclinations, helping unveil destinations or experiences previously overlooked (Santamaria-Granados, Mendoza-Moreno, and Ramirez-Gonzalez 2020). Moreover, tourism recommendation platforms assist businesses like hotels and tour providers in effectively pairing travellers with appealing destinations or activities (Mohamed Elyes Ben Haj Kbaier, 2018). Collectively, these systems serve as a potent tool for both travellers and travel-related businesses, fostering effortless travel experience discovery and crafting enriching journeys (Torres-Ruiz, 2018). Nonetheless, some experts argue that these systems might not consistently yield accurate or trustworthy recommendations (Petrevska and Koceski, 2012). This scepticism stems from the system's reliance on data and algorithms that might not holistically represent intricate individual preferences, sometimes achieving accuracy as low as 79% (Shafqat and Byun 2019). Traditional tour planning systems generally adopt a tripartite structure: delineating tourist profiles, assessing Points of Interest (POIs), and route optimisation. Parallel research showcases a methodology that permits tourists to define their interests via image collections, facilitating the system's deduction of their profile. Following the user's choices, the system consistently amends their dynamic profile, reaching accuracy levels of 78.4% (Konstantinos Pliakos, 2015). The system subsequently curates a resource list, boasting 90% accuracy, harmonised with both the user's profile and destination tourist resources (Linaza 2011). Nonetheless, there's potential system bias towards specific destinations or activities, which may stem from user demographic data or underlying algorithmic biases (Mehrbakhsh Nilashi, 2017).

Tourism recommendation systems are not devoid of challenges, including noise, erroneous or unsuitable data. Effective recommendation systems often necessitate copious user data. In data scarcity, the recommendations might be imprecise. Future potential for tourism recommendation systems lies in furnishing personalised suggestions, interoperability with various systems, synergy with social media, and mobile-centric optimisation through innovative categorisation techniques.

## 5 CONCLUSION

In conclusion, several salient points have emerged from the examination of the tourism recommendation system and the comparison of the AlexNet Classifier with the SVM algorithm:

- The AlexNet Classifier has proven to be more effective in tourism recommendations, achieving a superior accuracy rate of 97.20%.
- The SVM algorithm, while still effective, lagged behind with an accuracy rate of 92.45%.
- There is a broad consensus among researchers and industry practitioners that tourism recommendation systems, harnessing innovative categorisation techniques, significantly enhance the traveller experience by providing tailored suggestions.
- Personalised recommendations, derived from past behaviours and preferences, enable travellers to discover novel destinations and activities that might otherwise be overlooked.
- There's some caution within the industry, with concerns regarding the potential inaccuracies of recommendation systems, especially when there is insufficient or noisy data.
- Future prospects for tourism recommendation systems include their integration with social media platforms, optimisation for mobile use, and their potential to deliver increasingly tailored recommendations to users.

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