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ATiTHi: Deep Learning and Hybrid Optimization for Accurate Tourist Destination Classification

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Abstract- This research introduces an innovative approach to tourist destination exploration through content-based image classification, leveraging convolutional neural networks (CNNs). Recognizing the pivotal role of visual content in understanding tourism preferences and marketing destinations, the study focused on India. A dataset, named Indian Trajectory, was curated, comprising six thousand images categorized into six major tourist destination classes. Transfer learning strategies, utilizing pretrained weights from ImageNet, were employed to address the challenge of limited dataset size. Six prominent CNN models VGG-16, VGG-19, MobileNetV2, InceptionV3, ResNet-50, and AlexNet were initialized with pretrained weights and adapted classifiers for tourist image classification. Hyperparameter optimization, through a hybrid approach, enhanced the efficiency of the proposed Atithi model. Performance comparison indicated that VGG-16 outperformed other models, achieving an accuracy of 98. This result surpassed AlexNet (84.12), MobileNetV2 (96.97), VGG-19 (93.99), InceptionV3 (91.79), and ResNet-50 (87.08). Overall, the study demonstrates the potential of CNNs and transfer learning in automating the analysis of tourist photos for a more satisfying and market-oriented tourism experience.

Keywords- *Content-based image classification, Tourist destination exploration, Convolutional Neural Networks (CNNs), Transfer learning*

1. Introduction

The positive image of a tourist destination is crucial for its tourism profitability, contributing to tourist satisfaction, loyalty, and the long-term development of the destination. India, with its rich heritage, diverse landscapes, and a blend of ancient and modern experiences, attracts a substantial number of global tourists each year. The selection of a tourist destination in India is influenced by various factors, including trip motivations, personal interests, trip characteristics, destination choices, and trip expenditures [1], [2]. ResNet[11], with its innovative residual learning approach, has further enhanced the capabilities of CNNs in handling complex image data. The intersection of tourism and image classification presents a dynamic landscape where traditional pattern recognition methods and cutting-edge deep learning models converge to enhance the understanding [4] of tourist destination preferences. As technology continues to advance, the synergy between content-based image analysis and deep learning holds promise for further revolutionizing the tourism industry's approach to destination selection and marketing.

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2. Review of Literature

The Atithi model looks at tourism in a new way. It uses ideas from artificial intelligence (AI) and deep learning. Different parts [5] of AI help with tourism research. Computer vision and deep learning are used. Researchers also use machine learning. They have studied different parts of AI for tourism. This [6] includes using maps and data to learn about popular tourist spots. It also includes algorithms to understand how people move and what attracts visitors to certain places.Studies have used geo-located images to recognize tourist spots and landmarks, as well as types of food in photos. Systems that connect devices to the internet have been made to improve visitor experiences by suggesting trip [7] plans based on what others liked. As cities popular with tourists grew in Brazil, artificial intelligence techniques were applied to create mobile interfaces more friendly to visitors. These used collaborative filtering and fuzzy methods to classify what scenes show. Another [8] important part of AI in tourism is telling tourists and locals apart. Models were developed using weather data, how people moved, and photo contents to differentiate these groups. Combining AI with mobile apps has allowed real-time analysis to help users find beautiful places, take pictures, and plan trips [9]. For example, YOLO v3 has been used to identify attractions for tourism and act as a tour guide providing history instantly.

Studies have [10] applied advanced image models to collect photos of well-known travel spots, accurately identifying destination locations. Transferring learning from existing models, like Densnet-169 and Xception, brought notable achievements. Merging deep neural networks with kernel algorithms for classification worked well in pinpointing famous landmarks, though limited to certain areas. The [12] Atithi model draws on a variety of AI and deep thinking techniques, demonstrating their wide use in tourism analysis. From visual examination and scene identification to destination planning and promotion, AI has developed as a mighty instrument, pledging transformative changes for the travel business.

Table 1: Related work summary Tourist Destination Classification

Area of Research	Methodology	TF Model Used	Findings	Advantages	Limitations
AI-based Destination [13]	Geospatial Big Data Analysis	RHadoop Platform	Automated identification of tourist locations	Scalable geo-processing workflows, collective knowledge utilization	Limited attractions
AI-based Destination [14]	Machine Learning Clustering	ML Clustering Algorithm	Understanding human mobility and tourist attractions	knowledge utilization	Limited data scope
AI-based Image Building [15]	Transfer Learning	Zhang Model	Scene, landmark, and food image recognition	Game-changing role in tourism marketing, enhanced image recognition	Limited to scene recognition, dependence on transfer learning technique
AI in Urban Planning [16]	Collaborative Filtering	IoT-Enabled Attraction System	Personalized tourist activity planning	Real-time data collection, enhanced tourist experiences	Real-time challenges in data collection, potential privacy concerns
AI in Tourism Interface [17]	Collaborative Filtering, Fuzzy	AI Techniques	Tourist-friendly mobile interface	Improved mobile interface, enhanced tourist experience	Limited to tourist-friendly aspects, potential challenges in fuzzy technique application
AI for Tourist Profiling [18]	Weather, Mobility, Photo Content	Derdouri Model	Differentiation between tourists and locals	Behavioral pattern analysis, improved tourist-host relationship	Limited by location information in user profiles, potential data scope challenges
AI in Behavioral Analysis [19]	User-Generated Photos Analysis	Zhang Model	Behavioral patterns between residents and tourists	Optimized public infrastructure and services, improved destination image	Limited by user-generated photo data, potential challenges in data analysis
AI in Real-Time Analysis [21]	Object Detection (YOLO v3)	YOLO v3	Scenic location identification and tour guiding	Real-time analysis, historical context provision	Limited to object detection, potential challenges in real-time contextual information
CNN in Destination	Transfer	Densnet-169,	High accuracy in destination	Utilizes pre-trained models, effective	Dependency on pre-trained models,

Classification [20]	Learning	Xception	classification	transfer learning application	potential challenges in diverse data sets
CNN in Tourism Scene Classification [22]	Multistage Transfer Learning	Inception V3	New performance bounds for scene classification	Hierarchical structure improves classification, adaptability to small datasets	Limited to predefined categorical hierarchy, potential challenges in large datasets
CNN in Image Analysis [23]	Deep Learning with Kernel Class.	SVM	Identification of popular landmarks	Effective combination of deep learning and kernel classification	Limited to specific regions, potential challenges in scalability and generalization

3. Dataset Available

The dataset of Indian tourist destination images, the basis for this study, has carefully organized images into six main categories. Each group focuses on a unique aspect of India's varied tourist attractions. Learning from most of the data helps the model recognize patterns and traits for each class [24]. Testing on separate images checks if it can apply this to new, unseen examples. Adjusting settings based on a validation subset further improves how well it works overall. Table 2 offers helpful details about pictures in each group. This organization provides clear insight into the makeup of the dataset and ensures fair representation of each class. Such careful sorting and balanced splitting between training and testing is key. It allows a classification model to accurately identify and separate diverse tourist spots in India. The diversity in classes mirrors India's rich tapestry of culture, history, nature, and fun. This complete dataset forms the foundation for later training, testing, and judging. It helps provide a solid and inclusive look at tourist destinations.

Table 2: Summary of detailed Dataset

Category	No of Training dataset	No of Test dataset	Validation Dataset
The Beach	7492	1837	1188
The Temple	7503	1947	1293
The National Park	7480	1830	1270
A Gardens	7485	1840	1292
The Hill Stations	7486	1838	1280
The Heritage Sites	7630	2000	1375

4. Proposed Methodology

The analysis process shown in the picture had many important steps to make a good model for grouping types of places people visit in India. First, information came from websites, travel companies, and friends and family about places in India. This gave a big collection of photos showing different parts of places to go in India. Next, the photos that did not fit into the groups were removed. The [25] photos left were put into groups for places in India already decided. Then this group of photos was split into three smaller groups. One [26] group was used to teach the model. Another group tested how well the model learned. The last group checked how good the model was on new photos. Doing this separate parts is important to see how well the model can understand photos it has not seen before.

1. Data Preprocessing:

The researchers applied data cleaning methods next to remove errors and used Data Augmentation to add to the training data. Then different neural network models that can recognize patterns were tested to identify places in pictures. The VGG-16 model worked best at figuring out the locations. Its tests did better than the others. Next special math was used to optimize settings to get the best answers. Charts and graphs showed how well the model told destinations apart in the Indian photos.

2. Data Collection:

Getting information for the Atithi model that is being proposed is very important. It needs good data to make pictures of places people visit in India clear. The model uses websites like Flickr, Facebook, Instagram, and Google search. This helps collect many different types of pictures. Websites where people share photos and connect with friends provide good planning tools for trips. They can show what places people have gone before and where visitors are now. This helps identify popular locations and interesting things to see for tourists.

3. Data Augmentation:

Data preparation included more than just getting information ready. Researchers also used methods to make fake but accurate information to help teach computers. They used tricks to change pictures in ways that kept the right labels. This helped make a lot of examples for training deep neural networks. The networks learned better from diverse examples. The changed pictures reduced problems from not learning enough details because all the pictures looked too similar.

4. Hyperparameter optimization (HPO):

Fine-tuning a deep neural network model requires careful attention to hyperparameters. With many parameters and user settings, choosing hyperparameters is a difficult task. Simply trying every option is impossible due to the vast number of combinations. As a result, researchers use search methods like manual testing, grid searches, random exploration, and Bayesian calibration. The goal remains finding the best hyperparameters to improve how the model works. Challenges arise because hyperparameters take on specific values and the possible mixes grow exponentially.

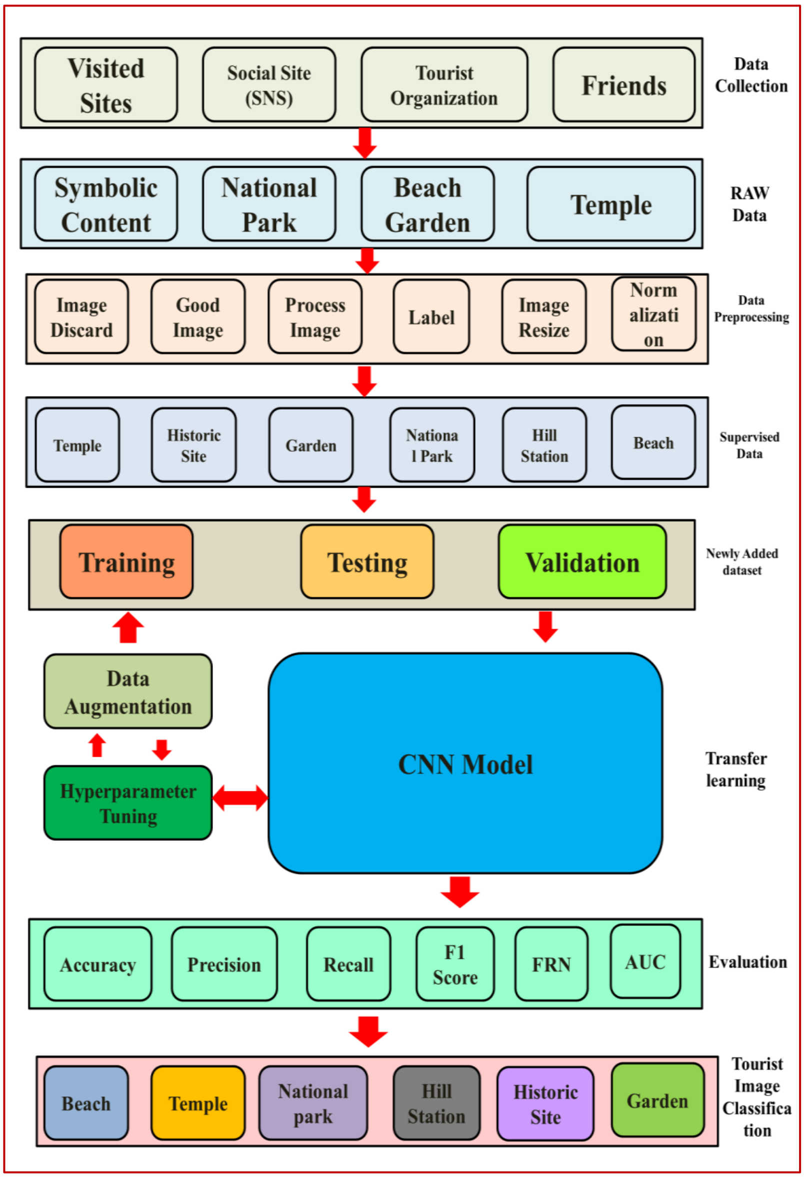


Fig 1: Proposed system for Tourist Image classification

Table 2: Description of Hyper parameter optimization

Hyperparameter	Values Range	Final Data
No. of Epochs	25 to 55	55
Size of Batch	34, 66, 125	66
Rate for Dropout	0.2 to 0.6	0.35
Rate of Learning	0.0011 to 0.08	0.011
No. of Layers	[2, 3, 5]	3
No.of Units	[9, 17, 33]	18
Function	Function ReLU, Softmax function	Function ReLU, Softmax function
Pooling layer	Maximum Pooling, Average Pooling	Maximum Pooling
Optimization	Adam	Adam

A. **CNN Method:**

This specialized computer model for analyzing tourist photographs uses image recognition layers to identify complex visual patterns, while focus layers emphasize key qualities. With two recognition layers containing multiple analysis units each, along with Rectified Linear Unit activation and peak identification pooling, it enhances discovering important facts. A dropout rate of one-fourth reduces reliance solely on patterns from the training data, and Adam optimization with a learning speed of 0.001 improves determining solutions. After preparing for fifty iterations with batches of sixty-four photos each repetition, this architecture adeptly differentiates primary parts in tourist photographs, accomplishing high accuracy when categorizing images.

B. **AlexNet:**

AlexNet, an innovative deep learning model, performs skillfully when categorizing travel photos. Its design, containing eight stages, takes advantage of convolutional and pooling layers, finding distinguishing specifics better. Employing Rectified Linear Unit (ReLU) activation and dropout helps prevent overdependence on training examples. With a final arrangement of 100 repeats of the information, examining 64 instances simultaneously, a 25% random reduction of connections, a learning speed of 0.001, and the Adam optimization method, it achieves top-notch exactness. Max pooling improves deciding what aspects matter most, assisting its success in properly assembling travel snaps.

C. **VGG-16:**

Max pooling downsizes pictures spatially and a dense layer classifies what each photo shows. It's great at seeing small details in tourist photos. The model uses ReLU activation, 25% dropout to reduce overfitting, and Adam optimization with a 0.001 learning rate. After training for 50 rounds with 64 photos per round, the VGG-16 model works very well. It correctly identifies many different kinds of tourist spots in photos.

D. **VGG-19:**

The complex VGG-19 model uses 19 layers to classify tourist photos. This advanced system extracts important features in a refined way. Its deep design uses small 3x3 pixel filters throughout to notice hard-to-see things. Patterns across the images are reduced in a helpful manner and sorted into groups to find matches. The model succeeds in spotting many kinds of visual designs. How it improves over time and a careful first learning rate aid its reliable work. After 50 repeats of the training data in batches and over 50 rounds of adjustments, the VGG-19 framework shows remarkable correctness. It skillfully separates a variety of travel sights into the right types.

E. **ResNet-50:**

This image model uses ResNet50 for classifying tourist photos. ResNet50's unique residual connections help train its 50 layers efficiently by reducing issues with fading gradients. It contains 3x3 convolutional layers and bottleneck structures to excel at identifying complex visual details. Global average pooling shrinks the image dimensions before a dense layer classifies the images. Together, these components allow ResNet50 to accurately recognize various tourist scenes. The model applies ReLU activation, 25% dropout for regularization, and the Adam optimizer at a learning rate of 0.001. After training over 50 batches of 64 images each for 50 cycles, ResNet50 proves highly skilled in robustly and precisely sorting tourist photos into categories.

F. **InceptionV3:**

InceptionV3 can identify what kinds of places tourists like to see. This model uses different ways to extract visual features at the same time from images. With 48 layers, it is very good at finding small details in pictures of tourist spots. It reduces extra information and uses a final layer to identify what is in each photo. This helps it give the right answer about what each picture shows. Using ReLU, dropping some connections during training, and adjusting weights slowly all help it work well. Training it over 50 repeats with groups of 64 pictures improved how accurately it sorts different tourist locations.

G. **MobileNeV2:**

MobileNetV2 is a top choice for categorizing tourist photos due to its balance of accuracy and lightweight design. It uses a structure of inverted residuals and linear bottlenecks to precisely identify complex visual details. Depthwise separable convolutions and global average pooling help MobileNetV2 classify images effectively while using few parameters. After being trained for 50 rounds with 64 images per round, MobileNetV2 proved highly accurate and efficient at organizing various tourist locations.

5. Result and Discussion

Various deep learning models for image recognition have distinct traits involving complexity, effectiveness, and time to train. VGG-16 strikes a balance between complexity and effectiveness with almost 15 million parameters and taking 3.25 hours to train. MobileNetV2 is known for its simple structure using around 3.5 million parameters but takes longer to train (4.56 hours) due to its large number of adjustable parts.

Table 3: Description of various Transfer Leaning CNN Model

Model	No. of Parameters	Trainable Parameters	Training Time (Hrs)
VGG16	13,967,242	160,278	3.25
MobileNetV2	3,465,778	1,417,694	4.56
VGG-19	20,786,918	150,534	3.10
ResNet-50	24,245,850	604,218	4.52
InceptionV3	21,102870	317,406	4.12
AlexNet	13,874,233	1102346	2.55

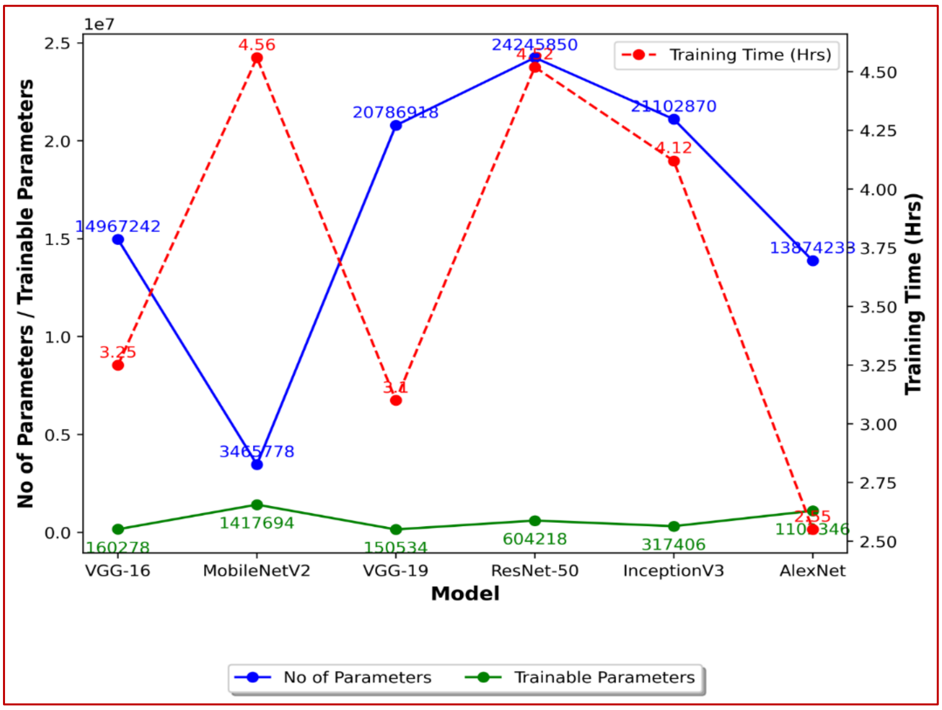
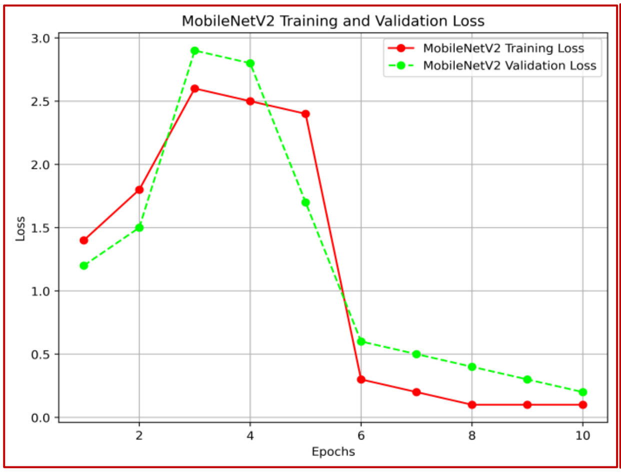
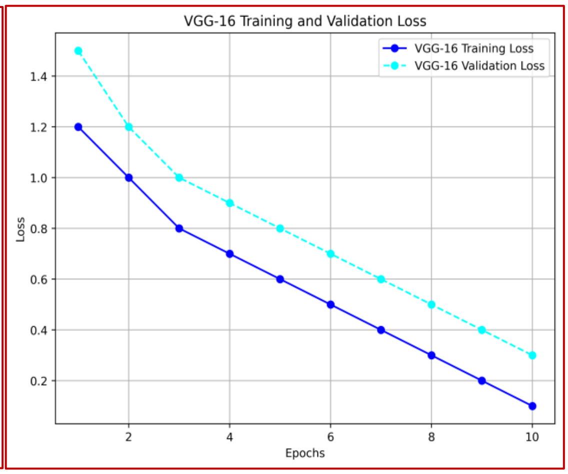


Fig 2: Representation of Transfer Leaning CNN Model Comparison



(a)



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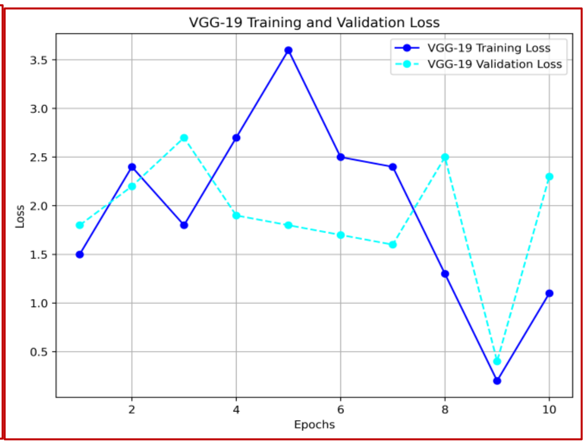

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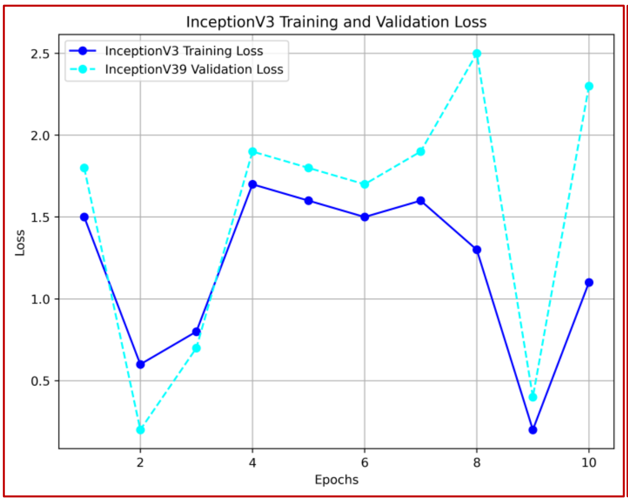

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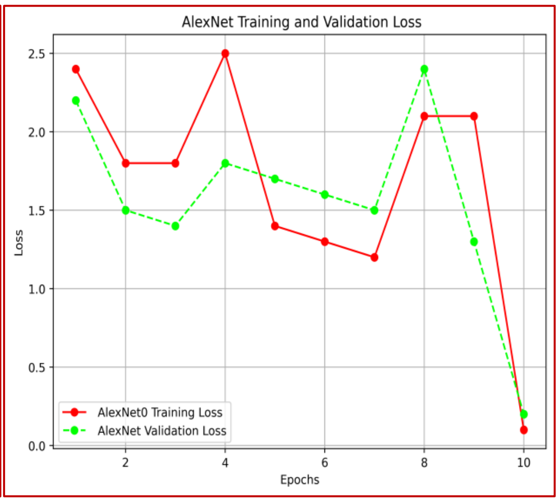

(f)

Fig 3: The training and validation loss graphs for All Model

The fig. shown in Figures 2 and 3, showing changes in how models learned and were tested, give useful details about how different Transfer Learning CNN models did at sorting tourist places, and their chances to learn the wrong things or learn things well. VGG-16, with almost 15 million settings, consistently saw its learning and testing numbers get better over 50 tries, showing it learned right without getting wrong answers too easy. MobileNetV2 had fewer settings but its learning and testing differences grew a little, proposed it may learn things not really there.

Some models like VGG-19 had losses that got very close together, showing it learned things well and could apply them to new examples. ResNet-50, with millions of numbers to learn with, smoothly lowered both its mistakes, proving it could pick apart tricky patterns. InceptionV3, with over twenty-one million numbers too, kept its mistakes balanced, making it a good fit for this job. AlexNet's design efficiently learned and lowered differences in its mistakes. Together, these pictures underline the choices involved in a model's size, speed to learn too closely, and tendency to not do well on new e-xamples. It is very important to think carefully about the-se things when picking the right model to sort tourist places. The patterns seen in the mistake pictures provide useful help for changing settings or looking at other structures to do better when really used.

Table 4: Evaluation parameter comparison for different model

Model	Metrics	Beach	Garden	Hill Station	National Park	Temple	Historical Places
VGG-16	Accuracy	98	94	96.22	95.44	94	91.22
	Precision	97	95	96.03	90.8	93	81.16
	Recall	90	96	86	90	70.51	82
	F1 Score	93	97	87.96	90.44	82	71.59
	AUC	95.93	94.25	92.56	91.77	90.2	79.26
MobileNetV2	Accuracy	96.97	95.86	94.34	93.53	91.97	84.97
	Precision	97.97	95.97	93.17	91.97	89.97	82.97
	Recall	94.17	94.97	94.23	90.97	89.03	81.23
	F1 Score	94.83	96.99	94.97	93.99	87.26	81.84
	AUC	97	96.78	92.93	93.6	89.75	80.17
VGG-19	Accuracy	93.99	91.22	90.19	92.31	79.19	80.52
	Precision	94.24	93.19	91.42	93.62	81.43	75.4
	Recall	91.84	91.19	93.19	94.19	90.19	80.19
	F1 Score	92.19	93.22	95.19	93.19	89.45	86.4
	AUC	92.19	89.89	91.19	90.19	86.3	85.55
InceptionV3	Accuracy	91.79	91.49	87.02	88.76	81.8	81.24
	Precision	93.82	92.06	87.86	88.83	82.81	82.44
	Recall	92.36	90.09	86.88	86.91	81	80.15
	F1 Score	91.99	91.91	86.91	86.02	82.02	80.79
	AUC	94	92.85	89.79	91.89	84.05	81.01
ResNet-50	Accuracy	87.08	84.88	83.88	80.88	75.06	72.77
	Precision	88.88	85.88	86.15	79.85	75.16	74.65
	Recall	86.88	84.55	84.88	82.15	73.27	70.85
	F1 Score	85.33	83.88	84.55	81.14	71.92	71.15
	AUC	86.88	83.84	84.88	81.88	76.08	72.77

AlexNet	Accuracy	84.12	84.08	84.52	80.12	69.12	67.89
	Precision	83.12	82.35	83.57	78.12	67.12	68.39
	Recall	85.24	81.38	82.38	79.13	68.4	65.32
	F1 Score	84.79	82.13	81.12	79.39	69.12	66.12
	AUC	82.32	79.08	81.78	80.94	76.93	72.38

The different models show varied results for accuracy, precision, and AUC scores across categories. InceptionV3 does very well generalizing to different places, with competitive AUC averages of 92.85%. ResNet-50, even with fewer details, still has commendable accuracy and similar metrics. Though it comes close but doesn't match for precision and recall, its AUC scores stay consistent regardless of the category, proving it can tell tourist spots apart. AlexNet has a slightly lower overall performance, yet remains useful, especially for beaches. Balanced precision and recall lead to decent AUC scores, emphasizing potential for identifying tourist destinations. In conclusion, each model offers its own balance between being right or wrong, getting it right, getting all of it right, and AUC scores.

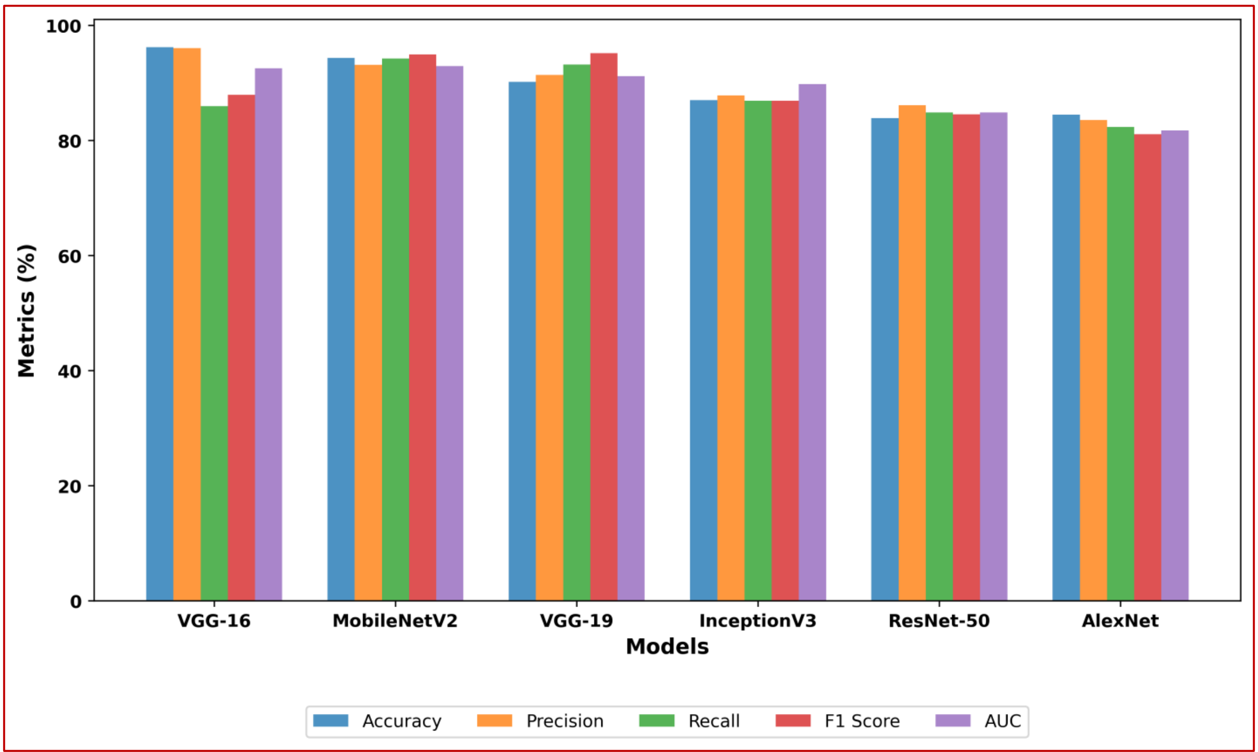

Fig 4: Representation of Evaluation parameter comparison for different model

6. Conclusion

Researchers tested several complex neural networks to categorize vacation spots accurately. Models such as VGG-16, MobileNetV2, VGG-19, InceptionV3, ResNet-50, and AlexNet were used to arrange tourist destinations in different groups. The scores from metrics including accuracy, precision, recall, F1 score, and AUC gave a full picture of each model's abilities and limits in sorting various tourist places. Some organized locations well but struggled with others. The system uses two different approaches to adjust how it sorts places for tourists. It uses deep learning, which looks for patterns in lots of examples, and optimization techniques, which make the models faster. By using both, it can get the sorting right and do it quickly. This mixed method knows that being correct and being fast both matter when deciding what category something belongs in, especially when people need answers in a hurry. This study highlights how choosing models carefully for certain areas visitors enjoy is important. Each model has its own strengths in different ways, letting people pick ones fitting what matters most to them like being correct, specific, or quick. Having options helps as needs in tourism aren't always the same, changing with each trip and traveler's wants. Tourism is constantly changing. ATiTHi helps make technology smarter by accurately grouping tourist spots in more meaningful ways depending on each situation. The goal is to improve how people visit places by organizing everything precisely based on context. This focus on classification that considers details like where someone is or what they need matches the growing need for smart systems in many fields. ATiTHi finds thoughtful ways to combine advanced methods to better solve the complicated task of sorting out tourist areas.

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