

Business Category Classification via Indistinctive Satellite Image Analysis Using Deep Learning

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Abstract—Satellite image analysis has numerous useful applications in various domains. Extracting their visual information has been made easier using remote sensing and deep learning technologies that intelligently interpret clear visual cues. However, satellite information has the potential for more complex tasks, such as recommending business locations and categories based on the implicit patterns and structures of the regions of interest. Nonetheless, this task is significantly more challenging due to the absence of obvious visual cues and the highly similar appearance of each location. This study aims to analyze satellite image similarity between business class categories and investigate the capabilities of state-of-the-art deep learning models for learning non-obvious visual cues. Specifically, a satellite image dataset is constructed using business locations and annotated with the business categories for image structural similarity analysis, followed by business category classification via fine-tuning of deep learning classifiers. The models are then analyzed by visualizing the features learned to determine if they could capture hidden information for such a task. Experiments show that business locations have significantly high SSIM regardless of categories, and deep learning models only recorded a top accuracy of 60%. However, feature visualization using Grad-CAM shows that the models learn biased features and disregard highly informative details such as roads. It is concluded that typical learning models and strategies are insufficient to effectively solve this complex visual problem; thus, further research should be done to formulate solutions for such non-obvious classifications with the potential to support business recommendation applications.

Keywords—Transfer learning; CNN; recommendation; scene classification; visual cue; road network; Grad-CAM.

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I. INTRODUCTION

Due to its ability to constantly monitor and capture detailed information of a certain location from the bird's eye view, Satellite Imagery is increasing in research interest, especially in the last few decades, for various domains. A wide range of applications in various domains, such as disaster response [1], [2], [3], [4], [5], [6], [7], agricultural decision-making [8], [9], [10], [11], [12], urban planning [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], recommendation system for business [23], environmental monitoring [24], [25], natural hazards detection [26], [27], [28], [29], [30] etc. have shown and proven the reliability and resourcefulness of remote sensing images for such analysis. The analysis of satellite imagery for the last few decades has seen various applicability of approaches when analyzing such datasets, among which the notable few are Land Use and Land Cover (LULC)

classification, object detection, scene classification, image fusion, segmentation etc.

Most of the analysis for machine learning and artificial intelligence parading requires lots of data since data is the source of information, and from that information, certain decisions are made based on the various use cases or applications. The most generic form for such analysis is structured data, which are comparatively easier to analyze. The generation and pre-processing of such structured data have disadvantages such as excessive time for data preparation, extensive labor and money for acquiring such data, privacy issues of customers' personal information, etc. So, various other forms of data, such as images and videos, have become quite popular for analyzing and implementing machine learning-based approaches. This research focuses on analyzing data with unstructured formats, such as images, to identify the hidden patterns in the spatial information. Also,

images contain rich contextual and hidden information that may not be readily available in structured data. Such hidden and contextual informative features must be extracted and analyzed further for various artificial intelligence- and machine learning-based applications. Informative imagery such as the ones mentioned has reduced the dependency of various analytics approaches solely on structured data. Due to the advancement in satellite technology and various commercial services, satellite images with medium or higher resolution, which was not common even a decade ago due to high cost or government restrictions, are quite easily accessible now with regular updates. Such remote-sensing images cover the entire world and are a good data source that can be analyzed for information retrieval. Various platforms and APIs allow free access to satellite image data. Our proposed research aims to effectively differentiate and categorize various businesses by analyzing and understanding hidden and contextual satellite image features.

Fields such as computer vision, pattern, and speech recognition have greatly succeeded in the last few decades by employing Deep Learning (DL) for such analysis. The research analyzes satellite imagery features to identify suitable businesses for a particular location. Each satellite image provides imagery of the neighborhood's surroundings with the POI in the center, and those features will be analyzed for insights regarding a business's suitability in a location. The research tries to analyze all the surrounding image features, such as properties, land features, etc., to gather insight into the visual appearance of a particular business's surroundings. Gathering information from hundreds of samples for one business category with deep model training allows us to extract the prominent features that usually surround a particular type of business. Such features will then be classified according to the business category. Then, from the satellite imagery of any location in Malaysia, it is possible to predict the most suitable business for that location by analyzing those surrounding image features. The images are labeled in the original dataset with the business category it belongs to, so categorizing those businesses by analyzing the surrounding image features extends the possibility of building a recommender system for businesses within Malaysia by analyzing satellite image features. Such imagery is not that distinctive and difficult to classify since all types of business surroundings are usually quite similar in visual appearance. Due to the non-obvious visual cues in those remote-sensing images, it is intrinsically essential to extract the hidden patterns or relationships from the features of those images. DL can effectively identify the non-linear and the non-trivial relationships and extract more complex abstractions as data representations in the higher layers. Extracting such complex patterns from such non-obvious images requires hours of feature engineering before it can be trained for learning. Deep learning eases the way through the generation of deep features from those images, and then the deep classifiers classify those images into different business categories based on those image features.

Specifically, our approach utilizes deep learning architecture to analyze and derive insights from the remote sensing data using four popular state-of-the-art convolutional architectures known as VGG16, ResNet50, InceptionV3, and Xception. These pre-trained networks are used as deep feature

extractors and classifiers to distinguish various categories from satellite images. Then, the models will be analyzed further by extracting the deep architecture layers and visualizing the output with the help of Grad-CAM to find out the patterns the model tries to emphasize for classifying these businesses. The intrinsic similarity or dissimilarity of the images will also be derived through metrics such as the Structural Similarity Index (SSIM), which indicates the structural similarity of the images. The output of the Grad-CAM visualization will inform us about the focus of the last convolutional layers and whether such a transfer learning approach is sufficient in deriving useful hidden cues from such complex images with non-obvious visual patterns. Various papers such as [31] and [32] already highlight some notable features, one of which is a survey from domain experts for retail location decision-making. So, the research will continue afterward with further investigation of some of the important hand-crafted features that can help the deep models gather more information before it can classify the business categories.

A. Literature Review

For the analysis of satellite imagery, the inclusion of various deep learning architectures is considerably new. Even though much research had been conducted with satellite imagery, most of the research was experimented on benchmark satellite datasets for classifying scenes of various land features or objects. On the other hand, many research papers, such as [33], researched retail recommendations with the help of deep learning but employed various important types of structured data consisting of information from demographics, geographical information, foot traffic, competition, accessibility etc. The utilization of satellite imagery for business site selection or recommendation, which is our approach, is quite rare to the best of our knowledge since the research requires the analysis of complex urban features of the business surroundings only from images to identify the suitable location for a business and the research requires such dataset that can provide latitude and longitude for those business locations. This section will summarize recent research conducted on satellite imagery to analyze the images further for location selection and scene classification or LULC classification approaches.

One of our most relevant research problems, conducted by [23], has employed satellite and urban data for business location selection using an attentive neural approach. The research comprises three satellite data sources: nighttime light intensity data, visible and near-infrared data, and RGB satellite images. The nighttime light intensity map refers to human-generated light intensity at nighttime and is composed of latitude, longitude, and intensity values. Visual and Infrared Radiometer (VIRR) data were gathered from Fengyun satellite VIRR sensors and consisted of a timestamp, geographic coordinates, emissivity, reflectance, Land Surface Temperature (LST), vegetation coverage (NDVI). RGB satellite images consist of the image, the geographic coordinates of the place in the image center, and the geographic range of the image [23]. The research also included Point of Interest (POI), road network and taxi trajectory data, and the satellite data mentioned above.

Other than the above research, the other papers mostly classify businesses from the remote sensing images, which can provide ranked businesses based on the prediction probability. The following research papers have conducted their experiment by implementing the multi-class classification on various scenes gathered from satellites. The satellite images contain the surrounding visual neighborhood information for a particular business. Classifying those scenes based on the nearby image features will justify the business's suitability for that location. The following section will summarize various satellite datasets utilized for such research and the research experiments with the scene classification approaches with the help of satellite images.

1) *Various Scene Classification Datasets*: Existing literature that has conducted their experiment on classifying satellite image scenes mostly utilizes some benchmark LULC datasets to the best of our knowledge. Among some of the popular LULC or scene classification datasets reviewed by this research, [34], [35], [36], [37] employed the UC Merced dataset, combining 21 different classes for their transfer learning-based scene classification problem. In contrast, WHU-RS dataset, consisting of 19 classes, took part in the experiment conducted by [35], [36]. Other than that, RSSCN7 – 7 classes, Aerial Image – 30 classes, NWPU-RESISC45 – 45 classes were also utilized by [37] for their deep learning-based comparative experiment using satellite images. [38] employed RGB EuroSAT images, consisting of 10 classes, for their comparative experimental analysis using VGG16 and ResNet50. Even though most of the scene classification approaches utilized benchmark datasets, such datasets are not suitable for real business scenarios where the images are much more diverse and have a lot more semantic variation, and are not reliable on specific land features such as trees, oceans, forests, agriculture etc. or objects such as golf course, overpass, airport, parking lot, tennis court etc. The proposed research aims to analyze the surrounding visual features from the bird's eye view of satellites to identify a particular business's suitability in a specific location. Analysis of surrounding complex urban planning features is required for this kind of research since most of the businesses are located in such places. To identify and analyze complex patterns in urban environments at a large scale, [39] generated a new dataset for such analysis consisting of 10 classes gathered with the help of Google Static Map API.

2) *Scene Classification Approaches*: [36] experimented using the pre-trained VGGNet architecture on UC Merced and WHU-RS datasets, two of the popular publicly available satellite imagery datasets for scene classification. In order to gain the benefits of multi-layer features, the pre-trained VGGNet has been used as a deep feature extractor, and canonical correlation analysis fuses the features to the Support Vector Machine (SVM) which is used to classify scenes. Our research has also utilized Various transfer learning-based models, including VGG16. In the next approach, since there will be hand-crafted features for the model to learn better, a transfer learning-based model such as VGG16 would also be employed as a deep feature extractor in our scenario.

Another classification approach for land use by [39] highlighted the importance of leveraging satellite imagery at minimal cost to analyze urban environments where no ground

truth information is available. The deep features extracted from the satellite images are one of the reasons for utilizing deep learning since it learns from the model itself about the hidden patterns within images. Their experiment initiates an open dataset with over 140,000 samples with ten distinct categories in 6 different cities and provides encouraging outcomes for land use classification problems with the pre-trained VGGNet and ResNet50 architecture. A new dataset for the remote sensing applications has also been derived to implement their research since no similar dataset was available. A dataset containing satellite images for most of the businesses in Malaysia would be one of the first things for us to submit as well.

SKAL (Structured Key Area Localization)-based-two-stream architecture, has been employed in [37] where the global stream represents the entire scene, and the local stream is prepared by extracting key local areas from the image for their scene classification approaches for satellite imagery. The approach regarding the SKAL might be a good direction to experiment further, but from some of the samples of different classes within that research, similar to other research in this area, the distinguishable factor is quite obvious in all the images. However, as described earlier in the data exploration, our inter-class difference, on the other hand, is low. The experiment by [37] has been conducted on four different datasets containing 21, 7, 30, and 45 classes, respectively, in the UC Merced Land-Use Data Set, RSSCN7 Data Set, Aerial Image Data Set, and NWPURESISC45 Data Set with the help of widely utilized AlexNet, GoogleNet and ResNet18 architecture.

Another remote sensing scene classification with transfer learning incorporated a Spatial Pyramid Pooling (SPP) layer in place of max pooling after the fifth convolution in AlexNet architecture, considering different image sizes and multiscale spatial information of the scenes. The inclusion of SPP was a good approach by [35] due to its ability to consider multiscale spatial information of the scenes and different image sizes. Since our images are entirely square 600 by 600 pixels, considering SPP layers instead of max pooling is an overstretch. [35] had conducted this experiment on UC Merced, containing 21 classes, and WHU-RS, containing 19 different scene classes.

One of the review papers for Land Cover and Land Use Classification in satellite imagery summarized the current research conducted on this domain with some of the popular architectures such as InceptionV3, ResNet50V2, and VGG19 by [34]. Similar architectures such as VGG16, ResNet50, InceptionV3 have been employed in our experiments as well so far for the classification of business class categories. [34] had also compared the implemented model by implementing all of them on a common remote sensing dataset UC Merced in RGB color space.

A comparative study is also provided by [38] LULC classification with VGG16 and ResNet50 architecture customizing through gradient clapping, early stopping, adaptive learning rates, and augmentation on the RGB version of the EuroSAT dataset. The experimental results indicated ResNet50 to be better compared to VGG16 for such problems with Gaussian Blurring, Horizontal and vertical flip, Rotation and Resizing augmentation to be more effective than the original version. Based on our current preliminary findings,

ResNet50 performed slightly better than VGG16 in similar scene classification of satellite images. Some more transfer learning-based models, such as MobileNet, AlexNet, Inception, EfficientNet, Xception etc. could highlight a better comparison of LULC classification from the satellite imagery.

Based on the literature review, it is evident that the satellite imagery scene classification approach has garnered sufficient research interest, and various researchers have utilized this approach on various benchmark scene classification datasets. But even though our research follows the same classification approach, the main objective is not limited to focusing only on specific land features or specific objects, instead, it tries to capture a multitude of diverse features and encompasses a broader range of content. Analyzing all the surrounding urban development characteristics to learn from higher-level concepts is much broader and less precise. This makes the research quite challenging and requires a dataset that contains such business surrounding information rather than just a benchmark scene classification dataset.

II. MATERIALS AND METHOD

This study aims to analyze satellite image similarity between business class categories and investigate the capabilities of state-of-the-art deep learning models for learning non-obvious visual cues. The study constructs a satellite image dataset using business locations and annotates it with the business categories for image structural similarity analysis. The images are then classified into business categories via fine-tuning of deep learning classifiers. The models are then analyzed by visualizing the features learned to determine if they can capture hidden information for such a task.

A. Data Preparation

The first step in this research involves constructing a dataset that can be used to investigate and analyze the satellite images of different business categories. Existing benchmark satellite image datasets lack such applicability due to the unavailability of such labeled data for businesses in a particular country. The POI data gathered for this research holds information on the location with latitude and longitude values, along with the labels of businesses by business name, subcategory, and category. With the help of business location information in Malaysia, the satellite images for those locations are extracted and labeled according to the subcategories of the businesses. So, the final dataset holds information on the satellite view of all the businesses within Malaysia distributed within their business categories. The existing satellite image dataset fails to provide such satellite information. It focuses more on identifying various land features and objects, while existing research aims to analyze the surroundings of the businesses from those satellite images to differentiate the businesses based on those features.

B. Problem Formulation

The research aims to analyze the satellite image dataset for deriving the suitability of a particular business in a particular location. All the satellite images utilized for this research

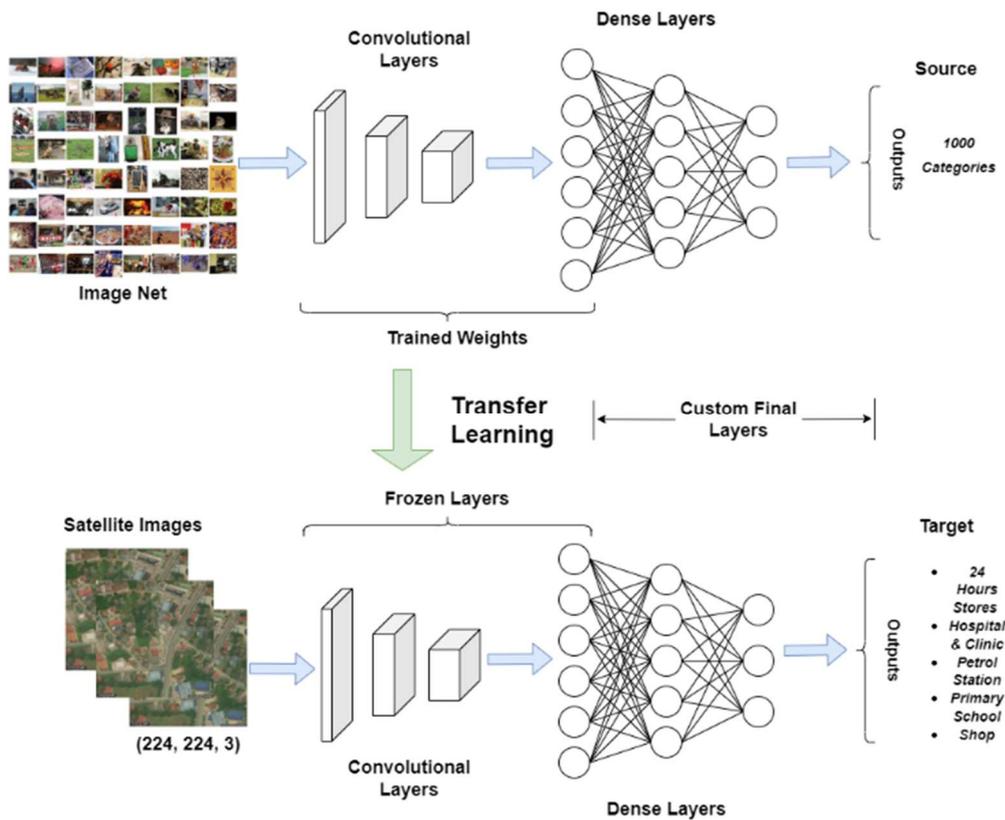
consist of the POIs and their surrounding neighborhoods from the top view. The main interest of this research is to explore these surrounding features so that the model can provide sufficient knowledge for a new location before a business can be recommended. The research aims to employ transfer learning-based models for the multi-class classification of the business subcategories. With the help of filtering, the deep models extract the most valuable information from these images and generate the features. The deep features from these models will then be forwarded to the deep classifiers for the final classification. The classification output will generate the probability values for the business classes with the help of analyzing the deep features. The highest probability implies the most suitable recommendation, while the lowest probability is the least suitable recommended business for that location. The classification output represents a ranking of businesses with the generated prediction probability values. So, each final model provides information on a business's highest to lowest suitability for a particular location.

C. Design Analysis

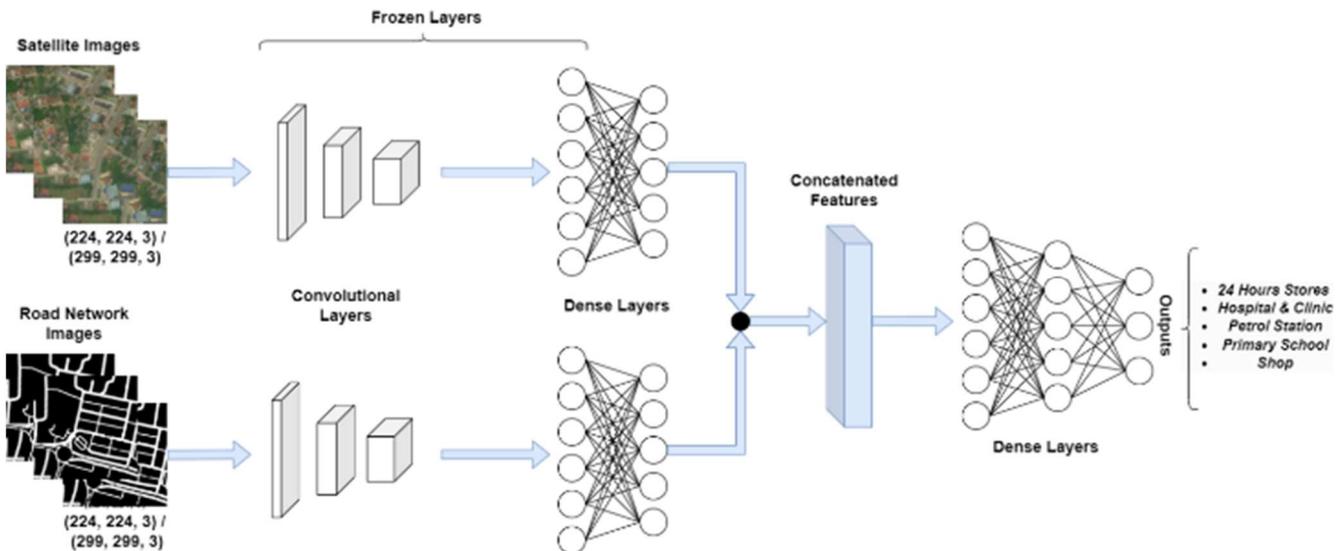
The following section demonstrates the approach for analyzing the remote sensing images and the description of the methodological approach for the research.

1) *Business Category Image Similarity*: One of the major challenges of this research is to derive meaningful insights from the satellite images due to the complexity of the segregation of the images among the business classes for classification. The satellite images appear visually similar for all the classes, making extracting implicit patterns and distinctive features much more difficult. SSIM has been derived from the business classes for the intra-class- and inter-class business classes to analyze the images' similarities or dissimilarities. The intra-class SSIM values represent the similarity or dissimilarity of the images for the same class, while inter-class SSIM values represent the same among all the combinations of classes. The experimental result for the measurement elaborates further in the later section, emphasizing why the classification of such images is extremely challenging despite employing deep learning to derive meaningful attributes from these images.

2) *Business Category Classification*: This section dissects the details of the approach for the whole transfer learning-based application for classification. At first, the dataset is split into a training and a testing set, with the training set being used to fine-tune the deep learning classifiers. The deep learning classifiers used in this research are state-of-the-art models widely used in image recognition tasks. They are first pre-trained on large-scale image datasets, such as ImageNet, and then fine-tuned on the business category dataset. The models are trained using a supervised learning approach, where the input to the model is an image, and the output is the business category label. The models are then evaluated on the testing set to determine their accuracy in categorizing satellite images based on their business categories.



(a) Approach 1: Learned Image Net Weights Applied on Satellite Images



(b) Approach 2: Learned Image Net Weights Applied on Both Satellite and Road Network Images

Fig. 1 Application of Learned Image Net Weights through Transfer Learning for Multi-Class Classification

With the help of transfer learning, the pre-trained weights from various established architectures help models learn better through knowledge transfer. The diagram in Fig. 1 demonstrates the overall flow of the approach with transfer learning. Two different approaches are being implemented using this transfer learning-based approach. The first approach utilizes only the information gathered from satellite images for the classification task. In contrast, the second approach includes the road network images along with the satellite images with the help of concatenation and then combines both features before the deep learning classifier can

be applied for classifying the business categories. Four pre-trained Convolution Neural Networks (CNN), namely VGG16, ResNet50, InceptionV3, and Xception have been chosen for this comparative experiment on this satellite imagery scene classification approach.

A very deep convolution network, VGG16, has proven the benefits of representation depth for classification accuracy. The performance degradation problem caused by adding more layers to sufficiently deep networks was tackled by ResNet via introducing Identity Shortcut Connection. The Wide Residual Networks are an improvement over the Residual

Networks. InceptionV3, belonging to the Inception family of convolutional neural network architectures, incorporates various enhancements such as encompassing the utilization of Label Smoothing, factorized 7×7 convolutions, and an auxiliary classifier that facilitates the propagation of label information deeper into the network. Xception is a convolutional neural network architecture that incorporates depth-wise Separable Convolutions. Developed by researchers at Google, it presents a new interpretation of Inception modules in convolutional neural networks. All the pre-trained models are trained on the popular ImageNet dataset, which has 1000 classes.

Learning rates of 0.0001 and 0.00001 have been experimented with the Adam and Stochastic Gradient Descent (SGD) optimization. In deep learning models, loss function for the classification is traditionally used, usually binary cross-entropy or multi-class cross-entropy. Since the proposed research experimented on multiple classes for classification, multi-class cross-entropy has been chosen for the classification approach on remote sensing images. An activation function is responsible for mapping the weighted input sum to the output of a neuron. It plays a crucial role in determining the threshold for neuron activation and the strength of the output signal. Rectified Linear Units (ReLU) are utilized for this research for the non-linear data transformation. At the same time, the SoftMax function is used as the last activation function for transforming the network's output into a probability distribution across the predicted output classes, ensuring normalization.

3) *Deep Features Visualization*: After the experimental implementation of the classification approach with transfer learning, we further analyze the focus of the applied models on various features of the images that the models emphasize learning. The Gradient-weighted Class Activation Maps (Grad-CAM) technique aims to visualize and interpret the decision-making process of deep learning networks during classification. Grad-CAM, developed by Selvaraju and colleagues, leverages the gradients of the classification score relative to the convolutional features generated by the network to gain insights into the crucial image regions for classification. The Grad-CAM observation suggests that the models try to gather insight from various biased features instead of obvious informative features like road patterns. The research continues with further experiments with those features to identify whether those road features can help the models learn more and provide better classification performance.

The research prepares a new dataset for analyzing satellite images with the help of deep learning to categorize businesses within Malaysia. Classification of the business category based only on satellite image features the potential for various demanding applications such as business recommendations. The proposed research will experiment and compare various transfer learning models for the multi-class classification approach and investigate the focal point of interest in the deep convolutional layer with the help of Grad-CAM.

III. RESULTS AND DISCUSSION

This section describes in detail all the experiments performed for the research and the resulting outcome for all

those experiments. The section starts by describing and exploring the dataset and then proceeds with the results of comparing various transfer learning models, visualizing the Grad-CAM output, and including road networks and all the experimental results.

A. Datasets

One of the significant tasks in the data science pipeline is collecting and processing the data before it can be utilized in the chosen model. Two different datasets have been collected for the project to analyze and further process: one contains the Latitude and Longitude values with the unique POI CODE, and the other contains the business name, subcategory, and category to the POI CODE, which can refer to the other dataset. As mentioned earlier, two different datasets were gathered for the project, the first consisting of various values, including the important latitude and longitude values, with the help of which the satellite images are being collected. The two datasets have one common key value: the POI CODE. With the help of this POI CODE, the two datasets are first outer joined and concatenated together. After merging the two datasets, there are lots of missing values, especially missing the business name, category, and subcategory. Since the business subcategory data would be used later for labeling the collected image data, missing values for those columns have been removed. From the final dataset, after removing the missing values, the remaining dataset is utilized later for the collection of image data.

The satellite images are gathered with the help of API services in the MapQuest Static Map API services. Fig. 2 below provides a wide satellite view of that location's surrounding neighborhood area, highlighting the roads, rivers, buildings, important destinations, etc. The images have been collected with the help of the latitude and longitude values from the POI dataset. Specifically, the images are gathered according to the Business Subcategory values from the POI dataset for reference later during classification. The gathered image size is 600x600 pixels with a zoom level of 18 from the MapQuest API. The images consist of three RGB color bands and five different business classes representing various business categories. So, the overall shape of the images is (600, 600, 3) for the satellite image. One thousand images per class for five classes have been experimented and so, in total, there are 5,000 images distributed in five business categories: 24 Hours Stores (24HS), Hospital & Clinic (HC), Petrol Station (PES), Primary School (PRS) and Shop (SH). The RGB version of the satellite image dataset collected with the abovementioned approach has been employed later for training purposes. The dataset has been split into an 80/20 split ratio for training and validation, respectively. Small batches of 50 images are used during the training process.

B. Structural Similarity of Satellite Imagery

This section continues further exploration of the satellite image dataset. The satellite images gathered from the POI data for the five distributed business categories were employed to implement this research further. Fig. 2 demonstrates the more significant scenario of a satellite image POI distribution. In the following image, Fig. 3, four imagery samples for four POIs are extracted. From those POIs, each one of them will represent a particular business category. For

demonstration, the red dot, surrounded by the blue squares, refers to a POI. Then, the satellite view of each POIs would be extracted separately and distributed based on the business category to which it belongs. The cropped images in Fig. 3 are the enlarged version of the POIs extracted using the API services in MapQuest. For a better comparison of how the satellite images look among different business class categories, samples for each category will be provided for a more precise understanding later.



Fig. 2 Collection of Satellite Images from Broader Satellite View



Fig. 3 Sample Cropped Images from Fig. 2 above of Various Business Category

Fig. 4 below demonstrates two sample satellite images for each class. The similarity of the images is quite apparent from the example images. Most images are random and have no pattern, even within the same class, complicating the research and making it quite challenging to distinguish one business from another.



Fig. 4 Example Satellite Images for Each Class

Other than just visually monitoring the similarity or dissimilarity of the images, the SSIM values have been gathered for some numerical representation of the hypothesis. The SSIM values range between -1 and 1, where 1 indicates the images are perfectly similar, while 0 indicates no similarity, and -1 represents perfect anti-correlation. The following heat map is generated based on those SSIM values from the five business classes being utilized in this research. There are two different segments for extracting these values: Intra-class SSIM values for every business class and the other. We calculated the inter-class for all the combinations of the

classes in those five business categories. From the SSIM values in Fig. 5, it can be observed that the values neither fall nor come even close between -1 and 1 for a perfect similarity or anti-correlation. Instead, all the values range between 0.07 and 0.17 for the intra-class and inter-class measurements.

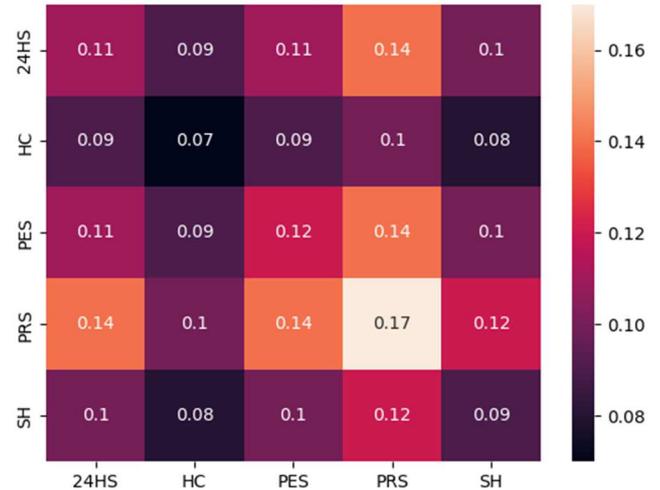


Fig. 5 Heat Map of the SSIM Values for Intra and Inter Class among All Classes

The intra-class SSIM values for “Primary School” class is the highest with 0.17 while “Hospital & Clinic” has the lowest SSIM measurement with only 0.07. For the inter-class, “24 Hours Stores” and “Primary School” along with “Petrol Station” and “Primary School” have the highest similarity in comparison with SSIM values of 0.14 while “Hospital & Clinic” and “Shop” have the lowest SSIM with average SSIM of only 0.08. Even though these values represent no similarity in comparison, the point to be noted here is that the values are incredibly close to one another, with the highest difference of SSIM values being only 0.10 for the intra-class and 0.06 for the inter-class. This measurement proves the hypothesis mentioned earlier regarding no patterns in the images, even not within the images within the same class. Due to this issue in the dataset, the research becomes extremely hard to differentiate the classes from one another while doing the classification.

C. Analysis of Classification Results

The following section illustrates the performance of four transfer learning-based models experimented on for the study and analyzes and experiments with some extracted features that help improve the learning of those models. Due to consistency while training all the models, the hyperparameters have been confirmed and fixed during the entire experiment. The only thing that differs among the models that have been experimented with is the input image size, which has been changed according to the default input image size for that particular transfer learning model. The default image size for VGG16 and ResNet50 is (224, 224) while the default image size for InceptionV3 and Xception model is (299, 299). The dataset has been split with an 80:20 ratio for training and validation, respectively. The split is random, and the model has been trained on 80% of the random dataset while it uses the remaining 20% of random images for validating the models.

TABLE I
COMPARATIVE CLASSIFICATION RESULTS OF TRANSFER LEARNING MODELS
ON SATELLITE IMAGES

Pre-trained Model	Image Size	Accuracy	Loss
VGG16	(224, 224)	0.50	2.16
ResNet50	(224, 224)	0.53	1.68
InceptionV3	(299, 299)	0.39	1.56
Xception	(299, 299)	0.39	1.84

We experimented with training the satellite images on four different architectures, as mentioned above, and the experimental results are displayed in Table 1. As explained earlier in methodology, the transfer learning model architectures for the whole experiment were fine-tuned by freezing the top layers, and only the classification layers that have been added are utilized for training the models. The table contains the validation accuracy and loss as the models' main performance metrics. The accuracy of the different experimental models stretches at most around 0.53 for the five-class classification approach, while the loss is around 1.5-2.2 on average for all the models after 20 epochs. While the accuracies of 0.39 – 0.53 for the models are quite low in comparison to various experiments that have been conducted on benchmark satellite image datasets such as EuroSAT, UC Merced, NWPU-RESISC45 etc., this only testifies the complexity of the dataset due to non-obvious visual cues and similar appearance of the satellite images for the various business categories.

The abovementioned datasets perform significantly better due to relying on specific land features such as buildings,

trees, oceans, forests, etc. On the other hand, this research employs and tries to learn from higher-level concepts consisting of the surroundings of the business area, which are broader and less precise. The research focuses more on capturing abstract urban planning perspectives than granular physical characteristics.

Moreover, the top-down view of the satellite imagery imposes specific challenges for the convolutional architectures since these models lack inherent rotational symmetry. This becomes particularly problematic when confronted with the complex layouts of urban environments as observed from a top-down perspective [39]. Also, satellite imagery varies significantly from natural images, which is also a crucial reason, mainly when transfer learning is used where the Image Net dataset consists of such natural images. Satellite images have a much higher degree of semantic variation than images of cats or flowers, which revolve around a central concept, and they encompass a broader range of content without a prominent focal point, capturing a multitude of diverse features, not a singular object. Despite the hurdles, the results obtained from the experiments are encouraging. The research is tackling a much more demanding problem of analyzing and focusing on higher-level subjective concepts about urban planning. Analyzing and extracting important hidden features from such satellite imagery extends the possibility of various useful applications. For further analysis of the performance of the models, Fig. 6 below demonstrates the confusion matrix for the four transfer learning models.

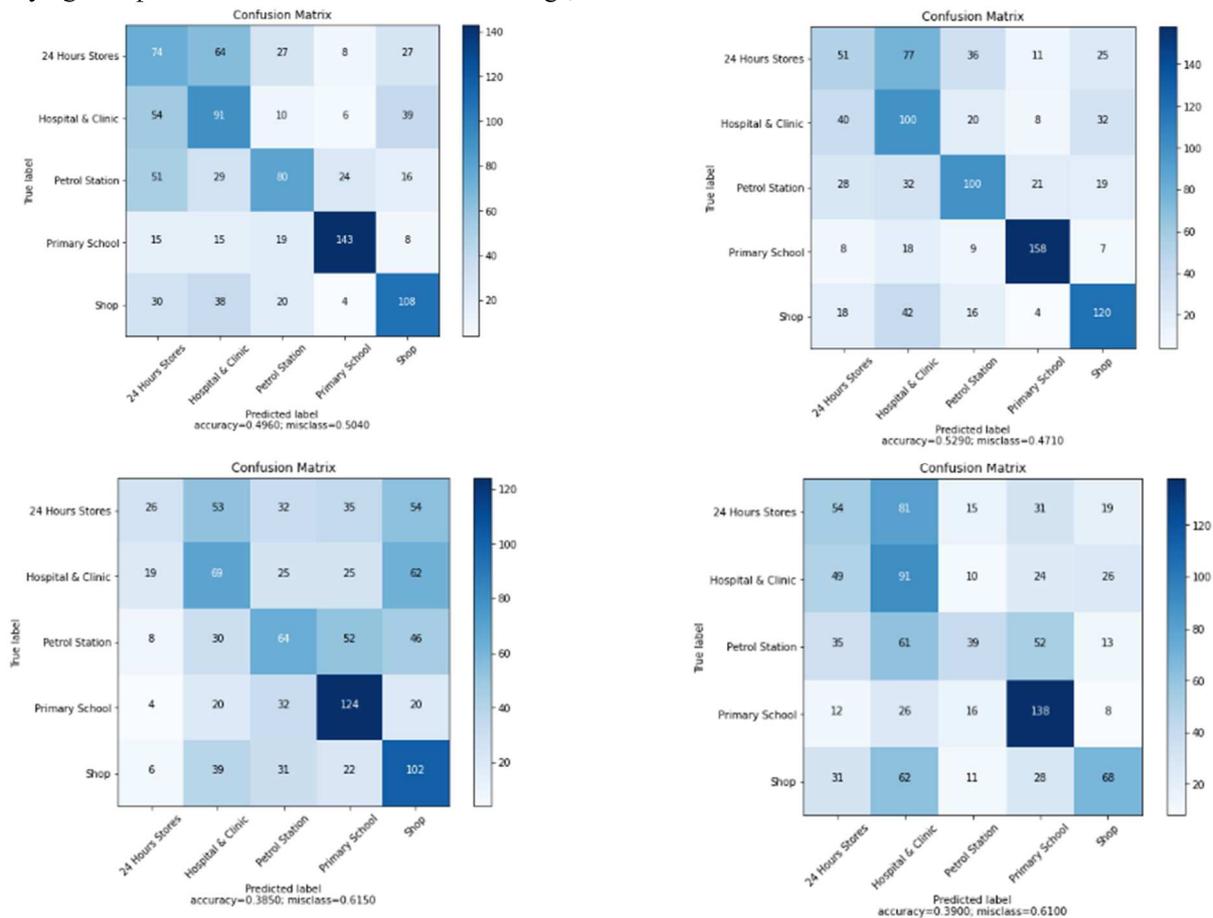


Fig. 6 Confusion Matrix of VGG16 (Top Left), ResNet50 (Top Right), InceptionV3 (Bottom Left) and Xception (Bottom Right)

The measurement shows that the “Primary School” class has the most correctly classified samples and is consistent for all the models. SSIM values are the highest for this class with a measurement of 0.17, implying more similarity than other classes. Class “Shop” also performs quite well for VGG16, ResNet50 and Inception while for Xception, it is getting confused mostly with “Hospital & Clinic”. “Hospital & Clinic” also performs reasonably well for most of the models. The worst performing class is “24 Hours Stores” on average and it is getting confused a lot with “Hospital & Clinic” and “Petrol Station”. Through the analysis of these classes using confusion matrix, it can be understood that the features generated through deep models are much more common because distinguishing one class from another is difficult. The only class where the correct classification is reasonably good and consistent is “Primary School” and after further analysis below on the density of roads, we identify one of the features that might be responsible for such an outcome.

The Gradient-weighted Class Activation Maps (Grad-CAM) technique aims to visualize and interpret the decision-making process of deep learning networks during classification. Grad-CAM, developed by Selvaraju and colleagues, leverages the gradients of the classification score relative to the convolutional features generated by the network to gain insights into the crucial image regions for classification. It generates heat-maps that provide visual explanations, aiding our understanding of how deep learning algorithms arrive at decisions. By employing the gradients of the classification score concerning the final convolutional feature map, Grad-CAM identifies the image areas that have the greatest impact on the classification score. These regions with significant gradients correspond to the locations where the final score heavily relies on the input data. The Grad-CAM function calculates the importance map by taking the derivative of the output from the reduction layer for a given class concerning a convolutional feature map. The Grad-CAM function automatically selects appropriate layers to compute the importance map for classification tasks. Some of the samples of the Grad-CAM outputs for all four models experimented with in this study are demonstrated in Fig. 7.

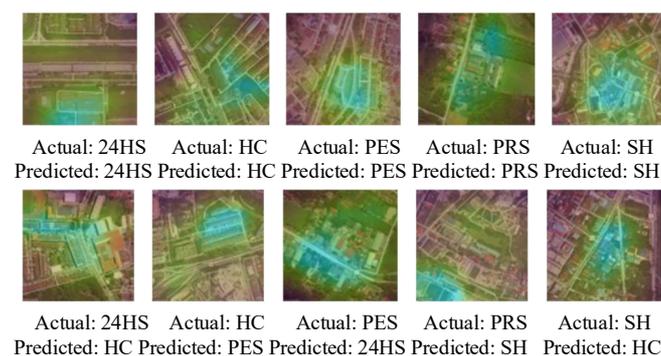


Fig. 7 Sample Grad-CAM Visualization for the Last Convolutional Layer of ResNet50 Model

We started by creating Grad-CAM heat-maps for the last convolutional layer in our model. In theory, the heat-map for this layer should display the most accurate visual explanation of the object being classified by the model. The outputs of the heat-maps are stored and monitored both for the actual and the predicted class labels. The Grad-CAM analysis shows that

the focus for most of the images is mostly on the most crowded section of the images, and it can be either congested buildings or roads in many of the scenarios. Other than that, there is no specific focus on objects or features from the images that might distinguish one class from another and help improve the model learning. So, further analysis and extraction of some features are carried out and then integrated into the model to see whether that impacts the learning of the models.

Fig. 7 above demonstrates the outputs of the Grad-CAM for the best-performing ResNet50 model for both the actual and predicted class labels. From the heat maps, it can be observed that the primal focus is mostly on the noisiest or most crowded centralized objects in the image instead of any specific distinguishable features for all the classes, which is why the differentiation of one particular class from the other based on these satellite image features are incredibly challenging.

D. Important Features for Business Site Selection

Using satellite imagery, numerous studies have emphasized the significance of urban planning features in site selection for businesses like retail, warehouse, and ambulance services. For instance, [40] considered road network data to identify suitable locations for ambulance stations, while [41] emphasized the importance of road and traffic networks in commercial site selection. [42] highlighted factors such as consumer group distribution, traffic network, and POIs as major influencers. [43] examined the correlation between street networks and the spatial distribution of retail stores, revealing the impact of street centrality on store locations. [44] employed a visual analytics approach using road network and GPS trajectory data for warehouse location selection. [23] integrated urban data, road network data, taxi trajectory data, and satellite data to determine optimal business locations. [45] also highlighted the importance of road networks, GPS trajectory, and POI data for selecting billboard locations. [46] integrated road networks as well during their optimal location analysis for parcel pick-up points in China. The road networks extracted from satellite images play a crucial role in this analysis. Fig. 8 displays sample road network images aligned with satellite imagery, illustrating their use in the experiment.



Fig. 8 Sample Satellite and Extracted Road Network Images

From the road networks, it can be observed that the formulation and density of the roads vary a lot. After extracting these road network images, further analysis needs

to be performed to derive meaningful results from these images. For this purpose, the density of the roads is calculated from all the five classes and then compared to see whether there are any specific patterns from such measurement.

From Fig. 9 below, it can be demonstrated that the density of roads does vary among the five business categories utilized for the study. The category “Primary School” has the lowest average density, with around 0.08 while “Hospital & Clinic” has the highest, with values close to .25. The density of the other three categories is quite similar to that of the latter. Now, it needs to be noted from the road density that even in the confusion matrix, as elaborated earlier, the lowest density of roads is for the class “Primary School”, which is much different compared to the other four classes. Also, the confusion matrix shows that the correct classification for “Primary School” is the most compared to the other four classes. So, it can be said that the variation in road density impacts the overall performance of the models, and that can be one of the distinguishable features for the five classes.

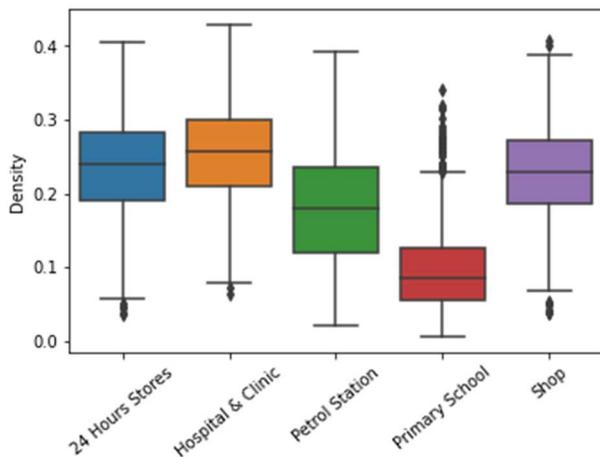


Fig. 9 Density of Roads for Five Business Categories

The road density for the other four classes is quite similar, and the misclassification for those classes is also quite high. All those other four classes are getting confused due to the similarity of generated deep features from the models. The SSIM values derived earlier for some preliminary exploration of the images also show that the values do not vary much among the different classes, meaning differentiating one class from another from the image features is exceedingly difficult for such images since the images are not visually similar for the intra-classes.

E. Classification Results Analysis after Road Feature Concatenation

Since some valuable and insightful patterns were gathered from the road network, we experimented with combining the features from satellite images and the road network. The proposed approach's method utilized satellite and road network images to train the deep learning models separately. Then, both the generated deep features from the two different models are concatenated, and a few more dense layers are added before the fully connected layer.

TABLE II
COMPARATIVE CLASSIFICATION RESULTS OF TRANSFER LEARNING MODELS ON SATELLITE AND ROAD NETWORK IMAGES

Pre-trained Model	Image Size	Accuracy	Loss
VGG16	(224, 224)	0.60	1.15
ResNet50	(224, 224)	0.57	1.29
InceptionV3	(299, 299)	0.53	1.31
Xception	(299, 299)	0.57	1.37

Table 2 above demonstrates the performance of the models for this concatenated feature approach. From the results, it can be observed that the performance of the VGG16 model is the best, with 60% accuracy, while Xception and ResNet50 both have 57% accuracy after ten epochs. In comparison, the improvement in the Xception model with the concatenated approach is quite high since the models trained only on satellite images yielded only around 39% accuracy for the Xception model. Now, the accuracy surge is around 18% more after the concatenation. The performance for VGG16 also increased by around 5% after only ten epochs, while ResNet50 and InceptionV3 also increased in performance up to 5% and 14%, respectively. The considerable improvement in the model performance, especially for the Xception and InceptionV3, shows that the road network images contain some valuable information and help the model learn better compared to features generated from satellite images only.

IV. CONCLUSION

The objective of the research was to investigate and explore the capabilities of innovative deep learning models in learning the non-obvious visual patterns from satellite images, which have the potential to solve various complex, demanding problems such as recommendation of business locations and categories based on implicit patterns and structures within the regions of interest. The experiments are performed on satellite imagery for the selected five business categories for multi-class classification with the help of transfer learning for this purpose. The satellite images are explored to analyze the structural similarity to gauge their similarity based on visual attributes. Subsequently, deep learning classifiers are fine-tuned for business category classification. The resulting models are thoroughly analyzed to ascertain their effectiveness in capturing hidden information essential for this task.

Experimental results reveal that business locations exhibit significantly high structural similarity regardless of their categories, indicating the challenges of distinguishing between them based solely on visual cues. The deep learning models for the first approach, which is trained on the satellite dataset, achieved a modest top accuracy of 53% for the ResNet50 model, while the rest are much lower in comparison. Visualizing the learned features using Grad-CAM makes it apparent that the models overlook highly informative details such as roads. Further analysis of the road networks is performed for experimental purposes. The density of the roads shows some variation in the categories; the class “Primary School” which has a much lower density than other classes, tends to perform a lot better in correctly classifying the samples, which can be seen from the confusion matrix.

Another approach includes the road network images and satellite images showing a reasonable surge in the model performance, especially for the Xception model. The other transfer learning models tend to learn more when satellite and road networks are utilized than satellite images. This observation suggests that conventional learning models and strategies are inadequate for solving this intricate visual problem. The extraction and analysis of some hand-crafted features from the images, instead of depending only on the generated deep features, may pave the way for much better learning for these models.

Further research is necessary to develop solutions for non-obvious classification tasks, particularly those that can support business recommendation applications. The current study highlights the limitations of existing approaches and emphasizes the need for novel techniques that can effectively leverage the implicit patterns and structures within satellite images. By addressing these challenges, researchers can potentially enhance the accuracy and reliability of business location and category recommendations, opening doors to new opportunities and applications in various domains.

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