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Original Research Paper

Brand Logos Recognition System Using Image Processing for Food and Beverage Brands

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Abstract: This study investigates the development of a Brand Logo Recognition (BLR) system employing Convolutional Neural Networks (CNNs), specifically designed for the food and beverage industry in Ipoh. Accurate logo recognition is vital for businesses to strengthen brand identity, monitor consumer engagement, and mitigate the misuse of counterfeit logos. Existing systems often encounter challenges related to variations in logo design, image quality, and lighting conditions. To address these issues, the research adopts a hybrid methodology that integrates the Machine Learning Life Cycle and the Software Development Life Cycle (SDLC), utilizing an iterative Agile development framework. The system incorporates CNN models for feature extraction and classification, complemented by Single Shot Detector (SSD) algorithms for object detection. A curated dataset of food and beverage logos underwent preprocessing techniques, including resizing, normalization, and augmentation, to enhance the model's generalization capabilities. Empirical results demonstrate high accuracy in detecting and classifying logos across diverse conditions, underscoring the effectiveness of the CNN-SSD architecture. The proposed system offers practical applications for marketing analytics and consumer research, empowering local businesses to refine branding strategies and improve customer engagement. Future research directions include the exploration of multi-label classification, real-time processing, and the integration of advanced methodologies, such as generative adversarial networks (GANs), for counterfeit logo detection. This study emphasizes the transformative potential of AI-driven logo recognition systems in revolutionizing marketing practices and supporting small and medium-sized enterprises (SMEs).

Keywords: Brand Logo Recognition, Convolutional Neural Networks, Deep Learning, Image Processing, Machine Learning.

1. Introduction

Logos are a fundamental element of a brand's identity, serving as a visual representation of the brand and its core values. Acting as crucial visual markers, logos significantly shape customers' perceptions, influence decision-making, and strengthen relationships with brands [1]. A well-designed and recognizable logo enhances brand awareness and fosters consumer loyalty, playing an essential role in differentiating brands within highly competitive markets [2]. In the food and beverage industry, the strategic deployment of logos has become increasingly important for building brand recognition and driving consumer engagement. However, effective recognition and identification of logos are often hindered by variations in design, image quality, and lighting conditions [3].

The advent of deep learning techniques has transformed the domain of image processing, providing enhanced accuracy and resilience. Among these techniques, Convolutional Neural Networks (CNNs) have demonstrated remarkable potential for applications such as logo recognition (LR) [4]. Traditional LR systems, which rely on manual or semi-automated feature extraction methods, often struggle with complex designs and variations, positioning deep learning-based approaches as a superior alternative. These advanced systems enable businesses to gain valuable insights into brand recognition and consumer loyalty, thereby refining their marketing strategies [5]. For example, accurate LR can help organizations better understand consumer preferences, optimize product designs, and evaluate the effectiveness of branding initiatives.

In the context of food and beverage brands, robust LR systems address several critical industry challenges. These include detecting counterfeit logos, analyzing consumer behavior, and supporting automated surveillance and fraud detection. Leveraging large datasets and advanced computational tools, CNN-based LR systems have demonstrated notable improvements in recognition accuracy, even for logos featuring intricate designs or diverse variations [6]. These advancements underscore the transformative potential of AI-driven technologies to revolutionize marketing practices and enhance customer satisfaction.

Ipoh, a town renowned for its vibrant food and beverage sector, provides an ideal setting for examining the application of CNN-based logo recognition systems. The development of such systems within this locale has the potential to support local businesses by optimizing branding strategies and driving the broader adoption of advanced technologies among small and medium-sized enterprises (SMEs). By employing deep learning methodologies, this research aims to create a Brand Logo Recognition (BLR) system tailored to the specific needs of food and beverage brands in Ipoh, thereby improving marketing efficiency and consumer engagement [3].

This article explores the capabilities of CNN-based BLR systems in addressing the challenges associated with logo recognition, particularly within the food and beverage industry. It examines the limitations of traditional methods, the advancements enabled by deep learning, and the practical implications of implementing such systems in real-world contexts. By investigating these dimensions, this study seeks to contribute to the expanding body of knowledge on AI-driven marketing tools and their role in fostering innovation and growth in the business sector [7].

2. Introduction

2.1. Overview of Brands Marketing

Brand marketing, particularly logo recognition, holds substantial economic significance in the contemporary business landscape [9]. It serves as a critical driver of business growth, facilitates the development of consumer loyalty, and contributes to the establishment of a sustainable competitive advantage. From an economic perspective, several aspects underscore the importance of brand marketing with a specific focus on logo recognition [10]:

1) Differentiation and Competitive Advantage
   Brand logo recognition plays a pivotal role in distinguishing companies from their competitors. A distinctive and easily identifiable logo allows businesses to establish a unique identity, effectively capturing consumer attention in a crowded marketplace. This differentiation not only strengthens brand presence but also provides a competitive advantage by fostering customer attraction and loyalty. Ultimately, a well-recognized logo contributes to increased sales and revenue growth, reinforcing the company’s market position and long-term success.
2) Brand Equity and Perceived Value
   Brand logo recognition significantly contributes to the development of brand equity, an intangible asset that encapsulates the value associated with a brand. A well-recognized and

trusted logo fosters positive brand associations, instilling consumer confidence and reinforcing perceptions of quality and reliability. As brand equity strengthens, the perceived value of the brand increases, enabling businesses to command premium pricing for their products or services. This heightened value translates into greater financial success, positioning the brand for sustained growth and competitive advantage.

3) Consumer Trust and Loyalty:
Effective brand logo recognition plays a crucial role in cultivating consumer trust and fostering brand loyalty. A recognizable and memorable logo generates a sense of familiarity and reliability, which strengthens consumers' emotional connections to the brand. When a brand logo elicits positive perceptions, consumers are more inclined to exhibit loyalty, resulting in repeat purchases and word-of-mouth advocacy. This loyal customer base not only contributes to consistent revenue streams but also enhances the brand's market reputation, further solidifying its competitive position.

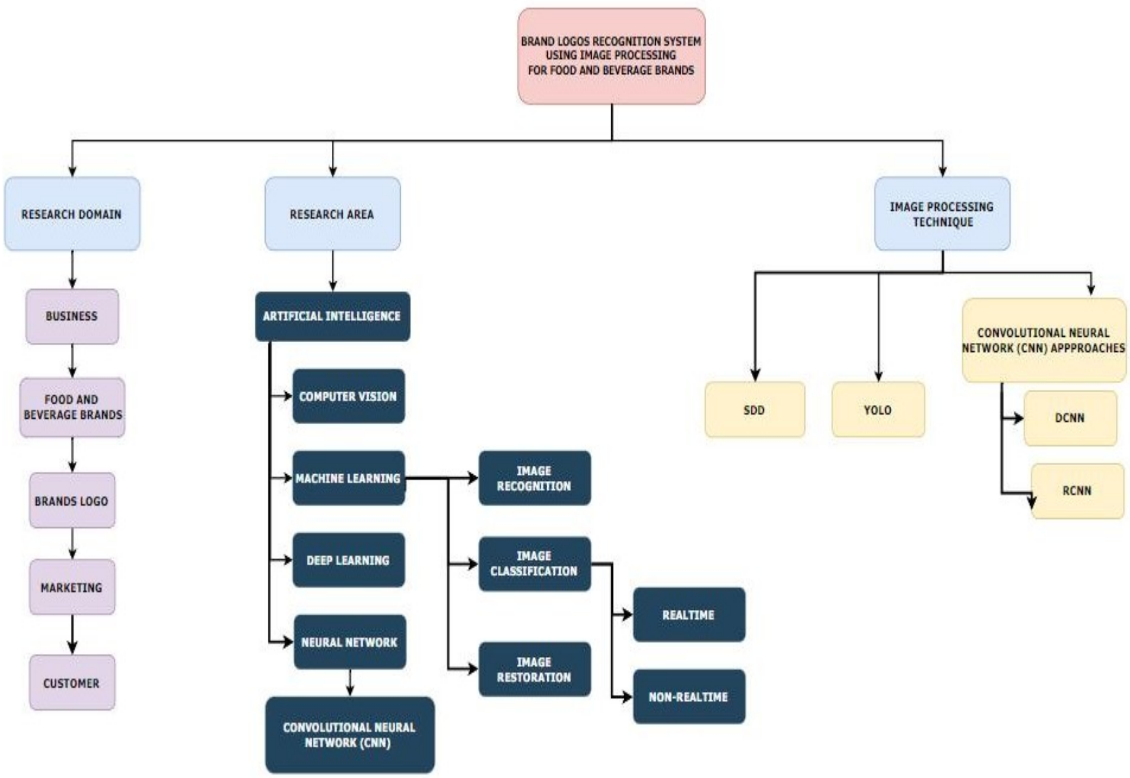

Figure 1. Conceptual Map for Brand Logos

Brand logos are visual representations that encapsulate the essence and identity of a brand. These carefully crafted symbols serve as powerful communication tools, embodying the personality, vision, and values of the brand [11]. A brand logo functions as the face of the brand, acting as a visual cue that instantly connects consumers to the brand's products or services. An effective logo is easily recognizable, memorable, and visually appealing, capturing consumer attention and leaving a lasting impression. Through design elements such as typography, colors, shapes, and symbols, a logo conveys critical information about the brand's industry, target audience, and unique selling proposition.

A primary function of a brand logo is to facilitate brand recognition. A well-designed logo fosters instant familiarity, enabling consumers to associate it with the brand's offerings [12], [13]. Acting as visual shorthand, the logo simplifies recall and differentiation from competitors. It serves as a visual anchor that evokes positive associations and emotions tied to the brand.

Beyond recognition, a logo plays a central role in establishing a brand's identity. It visually represents the brand's core values, positioning, and personality traits. For instance, a sleek and modern logo might signify innovation, while a warm and inviting design could convey trust and approachability. These visual elements create a conduit for emotional connections between the brand and its consumers.

Brand logos are integral to marketing and advertising strategies, prominently displayed across various touchpoints, including product packaging, websites, social media profiles, advertisements, and marketing collateral. Acting as a consistent visual thread, logos reinforce brand presence and enhance recall in the minds of consumers [7].

Furthermore, a well-designed logo fosters trust and credibility by symbolizing professionalism, reliability, and quality. It shapes consumer perceptions of the brand's offerings and can inspire confidence, encouraging consumers to choose the brand over its competitors.

2.2. Overview of Deep Learning and Neural Network and Image Recognition

This research focuses on the area of brand logo recognition through image recognition techniques. Image recognition has become a widely explored domain in artificial intelligence (AI) research. Since the advent of AI, many countries have invested significantly in advancing AI technologies, leading to remarkable developments across various fields [11]. AI encompasses multiple approaches, including machine learning and deep learning. For this research, we employ a machine learning-based approach to detect and recognize brand logos as part of the image recognition process.

Image recognition serves diverse purposes and spans varying fields and complexities [12]. At its core, image recognition involves identifying objects within an image and determining whether specific objects are present. When integrated with AI, image recognition methods can analyze images more comprehensively by identifying and deconstructing the objects within them. A practical example is Google Lens, an application that utilizes image recognition technology. By analyzing captured images, Google Lens identifies objects and provides accurate search results based on the image content. This capability exemplifies the practical utility of AI-powered image recognition in everyday applications.

Deep learning, a specialized branch of machine learning, has significantly advanced image recognition. It trains artificial neural networks with multiple layers to learn from large datasets. These neural networks, inspired by the biological structure of the human brain, consist of interconnected artificial neurons organized into layers. Convolutional Neural Networks (CNNs), a specific type of neural network, are particularly effective for image recognition tasks. They employ a distinct architecture comprising convolutional layers, pooling layers, and fully connected layers to extract features and classify images.

Training deep learning models for image recognition requires labeled datasets, enabling the network to identify patterns and features by iteratively adjusting its internal parameters based on these examples. Deep learning excels in automatic feature extraction and representation learning, significantly reducing the need for manual feature engineering. Its hierarchical learning capabilities allow for capturing intricate patterns and discriminative features, resulting in high accuracy and performance.

Transfer learning is another valuable technique in deep learning, where pre-trained models, trained on large-scale datasets, are fine-tuned for specific tasks. This method leverages the insights and knowledge acquired from previous tasks, facilitating faster training and improved performance, especially when working with limited labeled data [13].

Deep learning and neural networks have been applied across various domains, including medical imaging, security systems, autonomous vehicles, and content-based image retrieval. These technologies have revolutionized image recognition by enabling models to automatically learn and extract features from raw image data, yielding precise and efficient predictions. In the context of brand logo recognition, deep learning techniques hold immense potential for applications in marketing, retail, and consumer behavior analysis. By leveraging image processing and deep learning, businesses can enhance their understanding of branding strategies and consumer engagement, driving innovation and competitive advantage.

2.3. Convolutional Neural Network Approaches

2.3.1. D-CNN

D-CNN or Dilated Convolutional Neural Network, refers to a specific architecture within convolutional neural networks (CNNs) that integrates dilated convolutions. Dilated convolutions, also known as atrous convolutions, involve introducing gaps or skips between the kernel elements during the convolution process. In contrast, a conventional convolution operation entails a kernel sliding over the input image or feature map with a stride of 1, performing convolutions with neighboring pixels. While this captures local information effectively, it may lead to a loss of spatial resolution as the network depth increases [14].

Dilated convolutions mitigate this issue by inserting gaps between the kernel elements. By applying a dilation factor greater than 1, such as 2 or 3, the receptive field of the convolution operation is expanded without compromising spatial resolution. This mechanism enables the network to capture both local and global contextual information. D-CNNs leverage dilated convolutions to enhance the network's capacity to recognize larger contexts and long-range dependencies within the input data. By employing dilated convolutions across multiple layers, D-CNNs can efficiently process and extract features from images or sequences, facilitating the analysis of large receptive fields [15].

D-CNNs have proven effective in a wide range of computer vision tasks, including image classification, object detection, semantic segmentation, and image generation. These networks exhibit improved performance in capturing fine details, managing large-scale variations, and preserving spatial information, outperforming traditional CNN architectures [15].

2.3.2. R-CNN

R-CNN, or Region-based Convolutional Neural Network, was introduced in 2014 and represents a significant advancement in applying convolutional neural networks (CNNs) for object detection research. The R-CNN architecture comprises three main modules: region proposal, feature extractor, and classifier.

The region proposal module generates candidate bounding boxes, which are independent and categorized into potential regions of interest. These candidate regions are then extracted for further analysis. The feature extractor module utilizes a deep CNN, such as AlexNet, to extract features from each candidate region. AlexNet, which won the ImageNet classification competition, is used to generate a 4,096-element vector that characterizes the contents of the image. This vector is subsequently input into a linear Support Vector Machine (SVM) for classification, with one SVM trained for each known class [16]. This straightforward application of CNN effectively addresses object localization and recognition tasks.

However, a major disadvantage of R-CNN is its slow processing speed, which hampers its efficiency in image recognition tasks. To overcome this limitation, Fast R-CNN was developed to address the speed issues associated with R-CNN. Fast R-CNN improves upon R-CNN in three key areas. First, the output of the CNN is fully connected to a layer that generates two outputs: one for class predictions via a softmax layer, and another for bounding box predictions via a linear regression model [17]. This process is applied to each region of interest within an image multiple times, improving both speed and accuracy.

In summary, R-CNN provides a simple yet effective solution for object localization and recognition using CNN-based feature extraction, while Fast R-CNN optimizes the original architecture by enhancing processing speed and classification efficiency. Figure 2.7 illustrates the Fast R-CNN architecture and how the model operates on each candidate region.

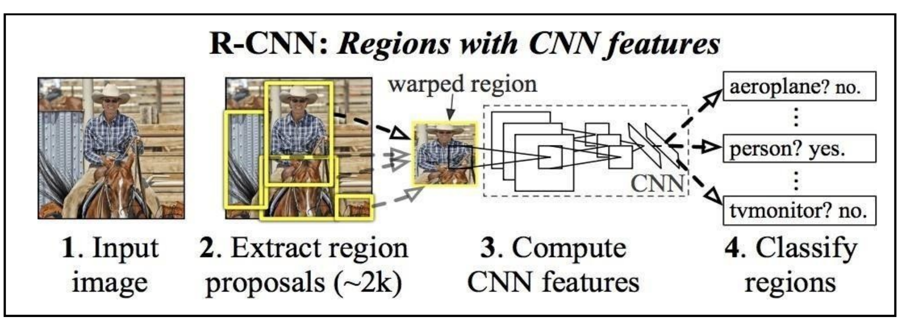

Figure 2. R-CNN Works

The primary purpose of Fast R-CNN is to significantly accelerate training and improve prediction accuracy compared to the original R-CNN technique. However, it still requires candidate regions alongside the input image for processing. Building upon this foundation, the development of Faster R-CNN further enhances both the speed of training and detection. This improvement is achieved through the introduction of the Region Proposal Network (RPN), which efficiently generates and refines region proposals during the training process [18]. Faster R-CNN comprises two key modules. The first module is a deep convolutional network that generates region proposals. The second module uses these proposed regions for detection through the Fast R-CNN detector [18]. By integrating region proposal generation directly into the network, Faster R-CNN eliminates the need for external region proposal algorithms, leading to a more streamlined and efficient object detection process

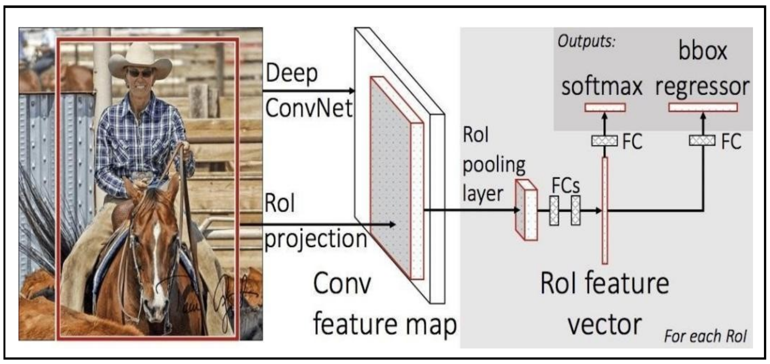

Figure 3. Fast-RCNN

In object detection, the entire system of Faster R-CNN is designed as a single, unified network. The Region Proposal Network (RPN) module directs the Fast R-CNN module on where to focus, utilizing the concept of 'attention' processes commonly seen in modern neural networks. For region proposal, the network's architecture and properties are crucial. Algorithms are developed to train both the RPN and Fast R-CNN modules using shared features, ensuring seamless integration [18]. The region proposal network works by taking an image of any size as input and producing rectangular object proposals as output. This process is fully convolutional, with the key goal being to share computation with the Fast R-CNN object detection module. A small network slides over the convolutional feature map, which is the output of the final shared convolutional layer, to generate region proposals. This smaller network processes the convolutional feature map to efficiently produce the proposals [18]. By leveraging shared computations, Faster R-CNN improves both speed and performance in object detection tasks.

3. Methodology

The methodology adopted in this research outlines a systematic approach for developing a brand logo recognition system using image processing techniques and machine learning, specifically Convolutional Neural Networks (CNN). The methodology is divided into three key phases:

3.1. Study of the Significance of Brand Logo Recognition Systems

This phase focuses on understanding the importance and potential applications of brand logo recognition, including its relevance in marketing, consumer behavior analysis, and automated image recognition tasks. This phase includes the following steps:

1) Defining the Problem Statement and Objectives: Establish the research area, significance, and scope of the system while addressing target users and potential benefits.
2) Literature Review: Utilize open-source tools (e.g., Google Scholar) and software like Mendeley to organize and study relevant academic works. Key focus areas include neural

networks, image recognition techniques, and practical applications in food and beverage sectors.

3) Preliminary Study: A survey is conducted to collect user feedback on the significance of logo recognition systems. A structured questionnaire covers respondents' experiences, expectations, and understanding of machine learning concepts.
   - Part A: Gathers demographic information (e.g., age, job, gender).
   - Part B: Evaluates perceptions of logo recognition systems, including business and consumer benefits.
   - Part C: Assesses knowledge of machine learning among users.

3.2. Development of the Brand Logo Recognition System

In this phase, the logo recognition system is developed using CNN-based image processing techniques. The system is trained on a dataset of brand logos to learn and identify distinct features associated with different logos, optimizing the model for accurate and efficient recognition.

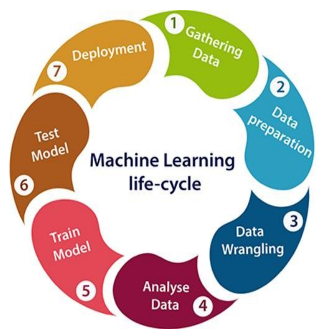

Figure 4. Hybrid Methodology – Machine Learning and SDLC

Steps in system development, are:

1) Research Initiation
   Define goals, objectives, and requirements for the software and machine learning components in collaboration with stakeholders.
2) Data Acquisition and Preparation
   Collect and preprocess a comprehensive dataset of food and beverage brand logos. Steps include resizing, normalization, and augmentation.
3) Agile Iterations
   Use iterative sprints for continuous software development, incorporating user stories and prioritizing tasks.
4) Model Development
   Train a CNN (e.g., ResNet or Inception) for logo classification and an SSD for object detection. Optimize using transfer learning and iterative experimentation.
5) Integration and Testing
   Combine machine learning models with software components, conducting unit and integration testing.
6) User Feedback
   Gather input to improve model accuracy and software functionality.
7) Deployment and Maintenance
   Incrementally release the system, monitor performance, and make updates to improve accuracy and address issues.

3.3. Construction of Algorithm for Brand Logo Recognition System

The algorithm construction process involves the following steps:

1) Dataset Collection
   Acquire a labeled dataset of F&B brand logos.
2) Data Preprocessing
   Resize, normalize, and augment images to enhance model generalization.

3) Model Training
   - Train a CNN model for feature extraction and classification.
   - Use an SSD for logo detection to identify bounding boxes and classify detected regions.
4) Logo Detection and Recognition
   Detect logos in input images using the SSD model, then classify detected regions with the CNN model.
5) Post-Processing
   Refine results with non-maximum suppression and confidence thresholds to reduce false positives.
6) Evaluation
   Assess model performance with metrics like precision, recall, and mean Average Precision (mAP).
7) Iteration
   Fine-tune hyperparameters and algorithms based on evaluation results.

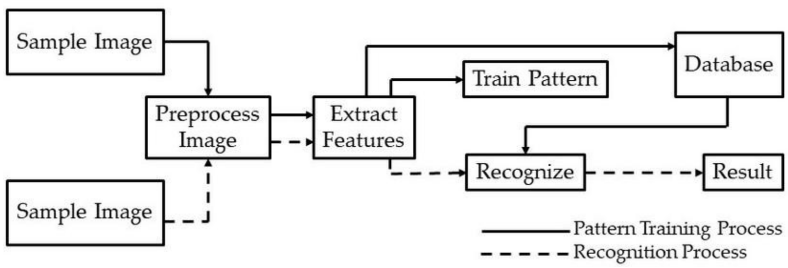

Figure 5. Construction of the Algorithm

3.4. System Architecture

The system architecture combines components for preprocessing, deep learning, user interaction, and data storage, as show in Figure 6.

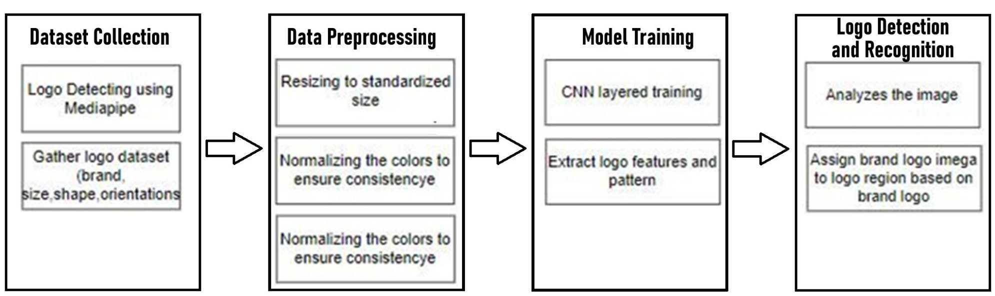

Figure 6. The architecture of the Algorithm

This architecture enables the system to process input images, identify logos, and deliver results efficiently. The system components are:

1) User Interface
   Allows users to upload or capture images for recognition.
2) Image Processing Module
   Standardizes image sizes, normalizes colors, and enhances quality.
3) Logo Recognition Algorithm
   Utilizes CNN and SSD for detection and classification.
4) Brand Logo Database

Stores logo information for verification and system improvement.

5) Integration Layer
   Ensures smooth communication between components.

4. Finding and Discussion

4.1. Findings

The implementation of a CNN-based Brand Logo Recognition (BLR) system in this study yielded several significant findings. First, the use of Convolutional Neural Networks (CNNs) demonstrated remarkable accuracy and robustness in recognizing food and beverage brand logos across various conditions, such as diverse lighting, image quality, and logo complexity. Training the CNN model on a well-preprocessed dataset enhanced generalization, minimizing both false positives and false negatives during logo recognition tasks.

Second, the study highlighted the critical role of integrating logo recognition algorithms with an efficient image preprocessing pipeline. By normalizing colors, resizing images, and applying data augmentation techniques, the system achieved consistent performance across a broad spectrum of input variations. These preprocessing steps were essential in enhancing the CNN's feature extraction capabilities, improving its overall performance.

Third, the deployment of the Single Shot Detector (SSD) in conjunction with CNNs for object detection significantly improved the system's ability to accurately localize and classify logos. This combination resulted in higher mean Average Precision (mAP) scores, effectively addressing challenges associated with identifying logos that have similar features or complex designs.

4.2. Discussion

The findings of this study underscore the effectiveness of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in overcoming the limitations of traditional feature extraction-based logo recognition systems. Traditional methods often face challenges when handling variations in logo designs and environmental conditions. In contrast, CNN-based systems utilize deep hierarchical representations, allowing for more accurate and robust logo detection across diverse scenarios.

A key point of discussion is the practical application of the Brand Logo Recognition (BLR) system for businesses in Ipoh. Local food and beverage enterprises can leverage this system to enhance brand recognition, monitor customer engagement, and combat the spread of counterfeit logos. This application not only supports marketing strategies but also helps protect brand integrity in a competitive market.

The integration of an iterative Agile methodology during the development phase was crucial in refining the BLR system. Continuous feedback from users enabled developers to improve model accuracy and optimize the user interface. This iterative process highlights the importance of user-centric approaches in creating AI-driven tools that are tailored to meet business needs.

Additionally, the research addressed challenges related to detecting counterfeit logos, which often imitate genuine brand designs. To mitigate this, the system incorporated advanced post-processing techniques such as non-maximum suppression and confidence thresholds. These measures effectively reduced false detections, enhancing the reliability of the recognition outcomes.

The role of transfer learning in this study was pivotal. By leveraging pre-trained CNN models like ResNet and fine-tuning them on the brand logo dataset, the system achieved optimal performance without requiring substantial computational resources. This approach demonstrates the cost-effectiveness and scalability of deep learning solutions, particularly beneficial for small and medium-sized enterprises (SMEs) with limited resources.

Finally, the study highlights the broader potential of deploying such systems in industries beyond food and beverages. Automated logo recognition can extend to sectors such as e-commerce, advertising, and trademark infringement detection, thereby transforming traditional business practices. The developed BLR system serves as a prototype for advancing AI applications in marketing and branding. Although the system is specific to Ipoh's food and beverage industry, the methodology and findings offer valuable insights for global applications. Future research could explore expanding the system's capabilities to multi-label classification and real-time processing to enable wider adoption.

5. Conclusion

This study successfully developed a CNN-based Brand Logo Recognition (BLR) system tailored to the needs of the food and beverage industry, particularly in the context of Ipoh. The findings demonstrated the effectiveness of Convolutional Neural Networks (CNNs) combined with Single Shot Detector (SSD) algorithms in accurately detecting and classifying brand logos under diverse conditions. Image preprocessing techniques, such as normalization, resizing, and augmentation, played a crucial role in enhancing the model's generalization capabilities, while iterative feedback through Agile methodology ensured that the system met user requirements. These results underscore the value of integrating deep learning techniques with practical development approaches to address real-world challenges in logo recognition.

The study also revealed the broader implications of deploying BLR systems for businesses. By leveraging accurate logo detection, local food and beverage enterprises can strengthen their branding strategies, monitor customer engagement, and prevent counterfeit logos from undermining their brand integrity. The cost-effective application of transfer learning, using pre-trained CNN models like ResNet, further highlights the feasibility of deploying advanced AI technologies in small and medium-sized enterprises (SMEs). These findings emphasize the potential for AI-driven tools to transform marketing practices, improve customer satisfaction, and safeguard brand identities across industries.

Future research should explore expanding the system's capabilities to address additional challenges. Potential directions include incorporating multi-label classification for recognizing multiple logos in a single image, improving real-time processing efficiency for broader applications, and extending the system to other sectors such as e-commerce and trademark infringement detection. Furthermore, integrating advanced techniques like generative adversarial networks (GANs) for counterfeit logo detection and expanding datasets to include logos from diverse industries will further enhance system accuracy and applicability. These advancements could pave the way for more comprehensive and scalable solutions, benefiting businesses globally.

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