SWARRNIM STARTUP AND INNOVATION UNIVERSITY

Bachelor of Computer Application

A Project Report On

Jewelry Classification

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ABSTRACT

This project focuses on the application of deep learning techniques, specifically utilizing the ResNet-50 architecture, for the classification of five distinct types of jewelry: necklace, earring, wristwatch, ring, and bracelet. The aim of the project was to develop a robust model capable of accurately categorizing these items based on their visual characteristics.

The dataset utilized for training and evaluation consisted of a diverse collection of images representing each jewelry category. Through a systematic approach to data preprocessing, model training, and validation, an accuracy of 77% was achieved on the test dataset.

Key components of the project included the implementation of transfer learning with ResNet-50, fine-tuning of model hyperparameters, and evaluation of performance metrics such as accuracy, precision, recall, and F1-score. Additionally, techniques such as data augmentation were employed to enhance model generalization and mitigate overfitting.

The results demonstrate the feasibility of using deep learning methods for jewelry classification tasks, with potential applications in e-commerce, inventory management, and visual search. Future work may involve further refinement of the model architecture, exploration of additional datasets, and investigation into real-time deployment for practical use cases.

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PROBLEM STATEMENT

The jewelry industry is characterized by a diverse array of products, including necklaces, earrings, wristwatches, rings, and bracelets. With the growing popularity of e-commerce platforms and the increasing demand for personalized shopping experiences, there is a pressing need for automated systems capable of accurately categorizing and classifying jewelry items based on their visual attributes.

Manual classification of jewelry items is time-consuming and prone to errors, hindering efficient inventory management, search functionality, and customer engagement. Traditional methods of categorization often rely on human judgment and subjective criteria, leading to inconsistencies and inefficiencies in the classification process.

To address these challenges, this project aims to develop a deep learning-based solution for automated jewelry classification. Specifically, the project focuses on the classification of five main types of jewelry: necklaces, earrings, wristwatches, rings, and bracelets. By leveraging deep learning techniques, such as convolutional neural networks (CNNs) and transfer learning, we seek to create a robust model capable of accurately distinguishing between different types of jewelry based on their visual features.

The successful implementation of an automated jewelry classification system has the potential to revolutionize various aspects of the industry, including online retail, inventory management, and customer experience. By streamlining the classification process and improving the accuracy of categorization, businesses can enhance product discoverability, optimize inventory allocation, and provide more tailored recommendations to customers.

INTRODUCTION

The jewelry industry has long been renowned for its intricate designs, timeless elegance, and cultural significance. From sparkling necklaces to delicate earrings, each piece tells a unique story and holds a special place in the hearts of consumers worldwide. With the advent of digital technology and the proliferation of e-commerce platforms, the way consumers interact with and purchase jewelry has undergone a profound transformation.

In today's fast-paced digital landscape, consumers expect seamless and personalized shopping experiences that cater to their individual preferences and tastes. However, the sheer diversity and complexity of jewelry products present a formidable challenge for online retailers and inventory managers. Manual classification of jewelry items is not only labor-intensive but also prone to inconsistencies and errors, leading to suboptimal customer experiences and operational inefficiencies.

To address these challenges, this project sets out to explore the potential of deep learning techniques for automated jewelry classification. By leveraging the power of convolutional neural networks (CNNs) and transfer learning, we aim to develop a robust model capable of accurately categorizing five main types of jewelry: necklaces, earrings, wristwatches, rings, and bracelets. Through the analysis of visual features extracted from jewelry images, our model seeks to replicate the human ability to discern and classify different types of jewelry items.

The significance of this research lies in its potential to revolutionize various aspects of the jewelry industry, from online retail to inventory management. An automated jewelry classification system would not only streamline the categorization process but also improve the accuracy and consistency of product classification. This, in turn, would enhance product discoverability, optimize inventory allocation, and enable more personalized recommendations for customers.

In the following sections, we will delve into the methodology employed in developing the classification model, discuss the dataset used for training and evaluation, present the results obtained, and conclude with insights into the implications of our findings and avenues for future research.

SYSTEM DESIGN

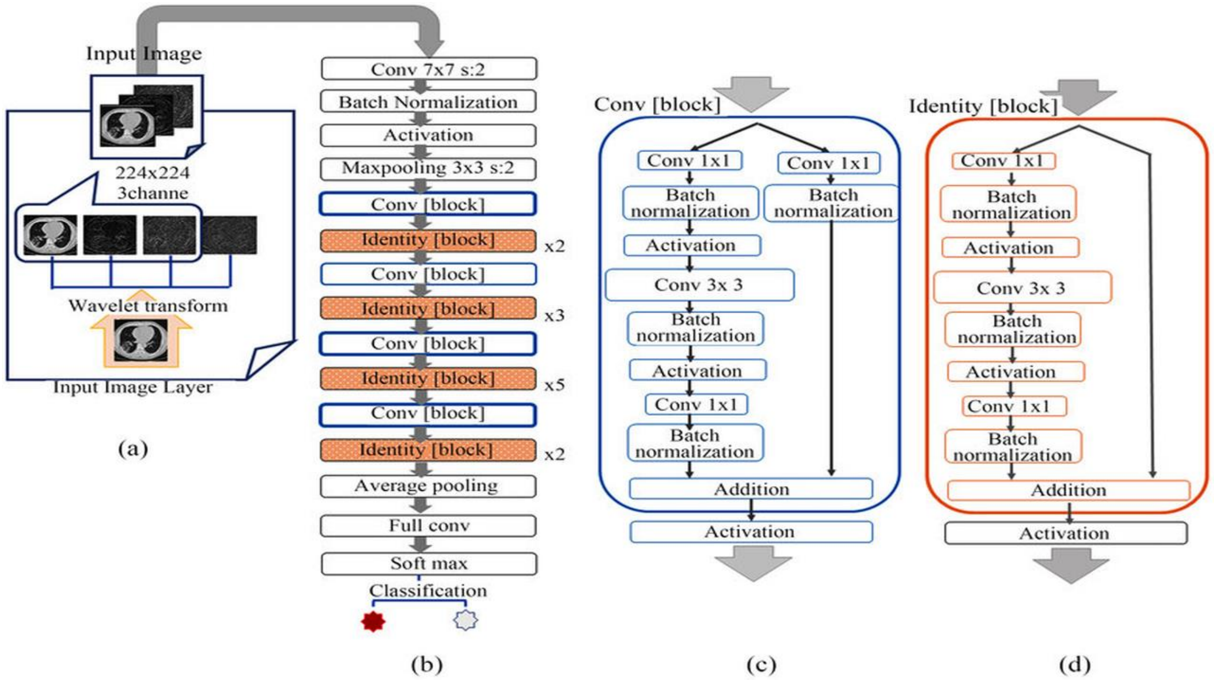
ResNet-50 is a deep convolutional neural network architecture that consists of 50 layers, including convolutional layers, pooling layers, fully connected layers, and shortcut connections.

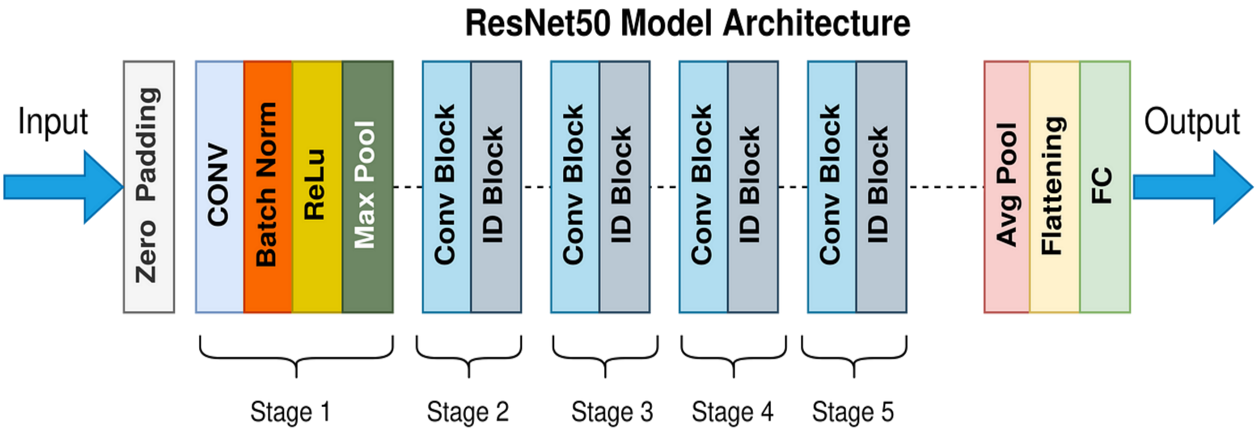
The main innovation introduced by ResNet-50 is the concept of residual learning, which addresses the problem of vanishing gradients in very deep networks. In traditional deep networks, as the number of layers increases, it becomes increasingly difficult to train the network due to the vanishing gradient problem. ResNet-50 tackles this issue by introducing shortcut connections, also known as skip connections or identity mappings, which allow the network to learn residual functions instead of directly learning underlying mappings.

These shortcut connections enable the network to bypass several layers, allowing for the direct flow of information from earlier layers to later layers. This helps to alleviate the vanishing gradient problem and enables the training of very deep networks more effectively.

The architecture of ResNet-50 consists of several blocks, each containing multiple convolutional layers followed by batch normalization and ReLU activation functions. The network gradually downsamples the spatial dimensions of the input through convolutional and pooling layers while increasing the number of feature maps. Finally, the feature maps are passed through global average pooling and a fully connected layer to produce the final output.

Overall, ResNet-50 is a powerful deep learning architecture that has been widely used for various computer vision tasks, including image classification, object detection, and image segmentation, due to its effectiveness in training very deep networks.





Key Features of ResNet-50

- ILSVRC’15 classification winner (3.57% top 5 error)
- 152 layer model for ImageNet
- Has other variants also (with 35, 50, 101 layers)
- Every ‘**residual block**’ has two 3×3 convolution layers
- No FC layer, except one last 1000 FC softmax layer for classification

- Global average pooling layer after the last convolution
- Batch Normalization after every convolution layer
- SGD + momentum (0.9)
- No dropout used

Advantages of ResNet-50 Over Other Networks

ResNet-50 has several advantages over other networks. One of the main advantages is its ability to train very deep networks with hundreds of layers.

This is made possible by the use of residual blocks and skip connections, which allow for the preservation of information from earlier layers.

Another advantage of ResNet-50 is its ability to achieve state-of-the-art results in a wide range of image-related tasks such as object detection, image classification, and image segmentation.

FUTURE PERSPECTIVE

The successful development of an automated jewelry classification system represents a significant milestone in leveraging deep learning for practical applications within the jewelry industry. However, there are several avenues for future research and development that could further enhance the capabilities and utility of such systems.

1.Enhanced Model Performance: Despite achieving a commendable accuracy rate of 77%, there is room for improvement in the performance of the classification model. Future research could focus on refining the model architecture, experimenting with different deep learning architectures, and exploring advanced techniques such as ensemble learning and attention mechanisms to further boost classification accuracy and robustness.

2. Expansion of Dataset and Classes: The effectiveness of deep learning models is heavily dependent on the quality and diversity of the training data. Expanding the dataset to include a broader range of jewelry styles, materials, and variations would enable the model to generalize better to real-world scenarios. Additionally, incorporating additional classes beyond the five main types of jewelry considered in this study could enhance the model's versatility and applicability.

3. Real-Time Deployment and Integration: While our focus has been primarily on model development and evaluation, the ultimate utility of an automated jewelry classification system lies in its seamless integration into existing e-commerce platforms and inventory management systems. Future efforts should explore the feasibility of deploying the model in real-time settings, optimizing inference speed, and addressing practical challenges related to scalability, latency, and resource constraints.

4. User Interface and User Experience (UI/UX): In addition to technical considerations, attention should be given to the design of user interfaces and user experiences that facilitate intuitive interaction with the classification system. Implementing user-friendly interfaces that allow users to easily search,

browse, and filter jewelry products based on visual attributes could significantly enhance the overall shopping experience and drive user engagement.

5. Integration with Augmented Reality (AR) and Virtual Reality (VR): The integration of automated jewelry classification systems with emerging technologies such as augmented reality (AR) and virtual reality (VR) presents exciting opportunities for enhancing the online shopping experience. By enabling customers to visualize jewelry products in virtual environments and even try them on virtually, AR and VR technologies can bridge the gap between online and offline shopping experiences, leading to increased customer satisfaction and conversion rates.

In conclusion, while this project has made significant strides in demonstrating the feasibility and potential of automated jewelry classification using deep learning techniques, there remains ample room for innovation and advancement. By addressing the aforementioned areas of future research, we can further unlock the transformative potential of artificial intelligence in revolutionizing the way we discover, explore, and interact with jewelry products in the digital age.

CONCLUSION

In conclusion, this project has demonstrated the feasibility and potential of employing deep learning techniques for automated jewelry classification. Through the development and evaluation of a classification model based on the ResNet-50 architecture, we have achieved a significant milestone in accurately categorizing five main types of jewelry: necklaces, earrings, wristwatches, rings, and bracelets. The model's performance, with an achieved accuracy of 77%, showcases the effectiveness of convolutional neural networks and transfer learning in handling complex visual classification tasks within the jewelry domain.

The implications of this research extend beyond the realm of academia, offering practical solutions to longstanding challenges faced by the jewelry industry. By automating the classification process, businesses can streamline inventory management, enhance product discoverability, and deliver more personalized shopping experiences to customers. Moreover, the integration of deep learning-based classification systems with e-commerce platforms holds promise for driving innovation and competitiveness in the digital marketplace.

Looking ahead, there are numerous opportunities for further innovation and refinement in automated jewelry classification systems. Future research efforts could focus on improving model performance, expanding the dataset, optimizing real-time deployment, and integrating with emerging technologies to enhance user experiences. By addressing these challenges, we can continue to harness the power of artificial intelligence to transform the way we interact with and experience jewelry products in the digital age.

In essence, this project represents a stepping stone towards realizing the full potential of deep learning in revolutionizing the jewelry industry. As we continue to push the boundaries of technological innovation, we remain committed to creating smarter, more efficient, and more immersive solutions that enhance the way we discover, appreciate, and engage with jewelry in an increasingly digital world.

REFRENCES

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