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Comparative Analysis of Jewellery Image Classification Using CNN, Class Imbalance techniques and Transfer Learning

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Abstract

The requirement of automated jewellery system is increasing with the widespread growth of e-commerce platforms. However, existing studies face challenges such as imbalanced and restricted dataset which affect models performance. This study presents a comparative analysis of different techniques focusing on improving accuracy and model stability. The dataset contains 490 images of ring and necklace. Four models are implemented, including Baseline CNN, Augmented CNN; Class weight CNN and Transfer learning using Mobile Net. The models performance is measured using different techniques like confusion metrics, accuracy, precision recall and precision–recall curve. The result indicates that transfer learning achieves 98% accuracy with balanced precision and recall. While both Augmented CNN and Class Weight CNN achieved 94% accuracy. Baseline CNN got 87% accuracy shows less stability and performance .These findings reveal that transfer learning performs best and effective in handling class imbalance.

Keyword: Jewellery Image Classification, Convolutional Neural Network (CNN), Data Augmentation, Class Imbalance, Mobile Net, Transfer Learning

1. Introduction

Jewellery plays an important role in the fashion industry, especially in countries like India. It is not only used for beauty and fashion but also has cultural and financial value. In today's digital world, jewellery is widely sold online, and a large number of jewellery images are uploaded on different websites and applications, like Amazon, Flipchart and some other online stores. It is very difficult and also time-consuming to manually manage and organize such a wide range of images. Therefore, there is a need for an automatic system that can classify, manage and organize jewellery images properly.

In recent years, deep learning techniques like CNN play a major role in image classification. Image classification is a process in which images are divided into multiple categories such as ring, necklace, bracelet etc. based on their features like shape, size and design.

CNN mimics the visual process of human visual cortex. This network extracts relevant features from the images through different techniques such as forward and backward propagation, by updating weights and biases. After that training and testing is applied to minimize the loss function and to improve the model performance [1].

1.1 Motivation

Previous studies shown the effectiveness of CNN based techniques in the jewellery and gemstone classification[2], [3], [4] . Despite of achieving high accuracy, there found many problems in existing studies. One of the major problem is class imbalance, means some classes have a large number of images while others have very few images, by which the model become bias, give wrong results and reduce the model performance. In addition, there found high similarities between different categories, due to the model get confused.

To solve these challenges or problems, CNN is use along with class imbalance techniques and transfer learning techniques, where CNN automatically extract features from the images class imbalance is handled using various techniques such as data augmentation and by applying class weights so that the model not became biased and transfer learning, which contains many pre-trained model, is used for improving feature extraction and to reduce training time.

The main objective is to develop jewellery image classification system using CNN, integrated with class imbalance handling techniques and transfer learning, and to compare different models and techniques, to improve accuracy and overall performance. The results or the performance of the proposed model is evaluated using confusion matrix or other matrices such as accuracy, recall, precision, F1-Score.This system will be beneficial for e-commerce platforms which make the categorization easy, and enhance efficiency and user-experience.

2. Literature Review

K. Vaibhav *et al.* (2019) focus on Indian jewellery classification using deep convolutional network, Google Net. It reduces the computation and improves network speed without affecting the accuracy. The dataset contain 8 categories of jewellery and total 700 images of these categories. Out of 192 test set images, 169 images are correctly classified. Overall 88% accuracy achieved using the Inception architecture [5].V Singh and P Kaewprapha use comparative CNN approaches to classify images and recognise them. First technique they use was SVM along with Alexnet. Secondly, they use Inception-v3 model. Total 5 categories were used in the dataset. At the end, it was found that Inception-v3 performed 0.9% better than the SVM. Overall accuracy of Inception-v3 is 99.13% [2].Similarly, one more study introduced automated jewellery identification and description generator system using deep learning techniques. Image captioning and encoder-decoder model were used. The model achieved more than 90% accuracy [3].B. Chakraborty *et al.* (2024) presented an automatic classification of 12 popular gemstones using CNN. The dataset contains 24000 images of these gemstones.70% training, 20% validating and 10% testing is done on the dataset. An accuracy of 98% was achieved by the proposed model[4].Meng et al. proposed a model which uses a database of jadeite images which was collected from different sources. They mainly focus on the jade quality.RestNet50, VGG,MobileNet models were used to categories jade type. Overall accuracy was 84.8% [6].Some classify the filigree jewellery based on the production method like handmade jewellery or mold product [7].This study provide a basic understanding of CNN based image classification how CNN automatically extract important features from the images and improve model performance [1].

3. Methodology

3.1 Data Collection: The dataset was collected from kaggle which has total 490 images[8]. From these, 189 images were of ring and 301 images were of necklace .The images are of jpg format. The dataset is imbalanced, which means the model can biased towards the majority class. The main purpose of this work is to classify jewellery images into two categories by handling class imbalance and using transfer learning. Further, Class Weight and data augmentation techniques used to handle the class imbalance.

Fig1. Ring and Necklace

3.2 Image Pre-processing: Image pre-processing is a technique where images are resized and normalized into fixed pixel size and specific range between 0 and 1 respectively [5].Minimum size of images was 90*90 pixels and max-Size was 267*275 pixels. Images were resized into 128*128 pixel dimension. Also the images were normalized from 0 to 255 range to 0-1 specific range. It improves the speed of model and helps model to learn important patterns from images.

3.3 Training and Testing: Dataset is split into training and testing set. Training set contains 70% and 30% is contained by validation and testing set of the images. From these 30%, 15% is for validation and 15% for test set.

3.4 Model Development: Four models were used for comparative analysis of jewellery image classification.

1. **Simple CNN Model:** A simple baseline CNN model is used. It consists of two Conv2D layers which have 32 and 64 filters which extract simple and deep features from the images respectively. MaxPooling layer which comes after these two layers is used to extract only the important features from the images and helps in reducing size and high computation. All these layers are then flatten into 1D vector form to pass them to a fully connected layer. This layer contains the activation functions like Relu, Sigmoid which helps to classify the images.
2. **Augmented CNN:** Image generator is a tool used to modify the images at the time of training and sent them to model. It contains the transformation like rotating images, zooming, flipping them, changing brightness level of images etc. By doing this, there occur multiple variations of a single image and the model thinks that the dataset is large. During training time, new images are generated in every batch and model learns new pattern from images and reduce over fitting problem. On the other hand, no images are generated during validation time so that the model can perform better on unseen data. But this does not change the class proportion due to which class imbalance problem remains.
3. **CNN with Class Weight:** To handle the class imbalance class weights are applied. The weights were assigned in such a way that ring class (0) got 1.298 weight and necklace

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class (1) got 0.813 weight. It indicates that more weight is given to minority class so that the model work on more balanced data and improves the model performance.

4. **MobileNetV2:** Finally a pre-trained model is used for better comparison. This model is already trained on huge ImageNet dataset. The main benefit of using this model is that initial layers are freeze to maintain the previous knowledge of model and only last layers were updated for a new problem. It increases training speed and improve performance of model.

3.5 Training Configuration:

The models were trained using Adam optimizer which helps in minimizing loss function and the problem was binary classification so binary cross-entropy loss function was used. Multiple epochs were used for model training also early stopping technique was used to stop training when the models stop showing improvement. It helps to prevent over-fitting.

3.6 Model Evaluation: Model evaluation is technique where we check the model's accuracy and performance using various terms or techniques like Confusion Metrics, Classification report, accuracy-loss graph and other visualization terms on unseen data.

Overall System Architecture:

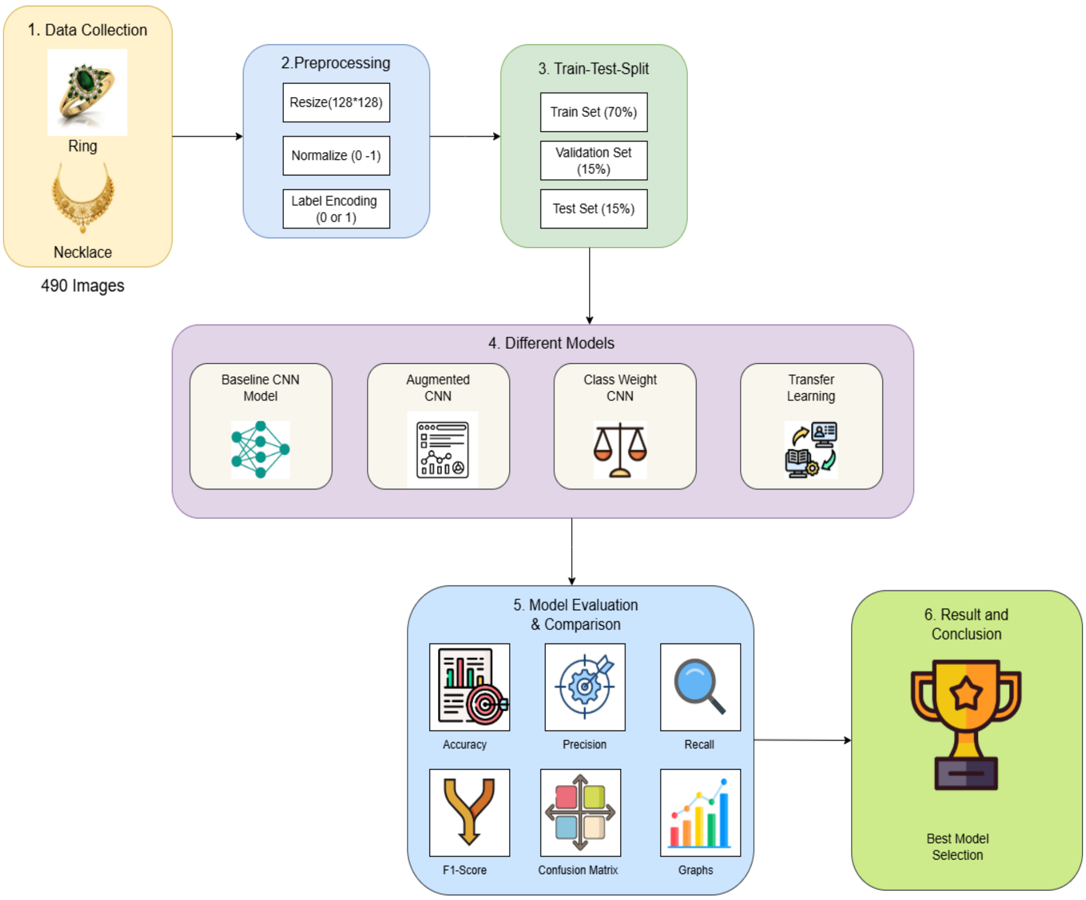

Fig2. Workflow diagram

4. Results and Discussion

A comparative analysis of four different models (Baseline CNN, Augmented CNN, Class Imbalance CNN, and Transfer Learning) is done in this work. To check the model performance, confusion matrix, accuracy graph and precision-recall curve are used.

Table1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Baseline CNN	0.87	0.84	0.97	0.90
Augmented CNN	0.94	0.97	0.93	0.95
Class Weight CNN	0.94	0.97	0.93	0.95
Transfer Learning	0.98	1.00	0.97	0.98

In Table1, the baseline CNN model achieved approx. 87% accuracy with high recall (0.97) and low precision (0.84). Augmented CNN got 94% accuracy with balance precision and recall indicating that data enhancement makes the model generalized and improve performance. Class Weight CNN model used to handle the class imbalance but it shows that class imbalance wasn't the main problem. This model presents same results as Augmented CNN. Transfer learning model (MobileNetV2) achieved best performance among all models with 98% accuracy with high precision of 1.00 and recall of 0.97.

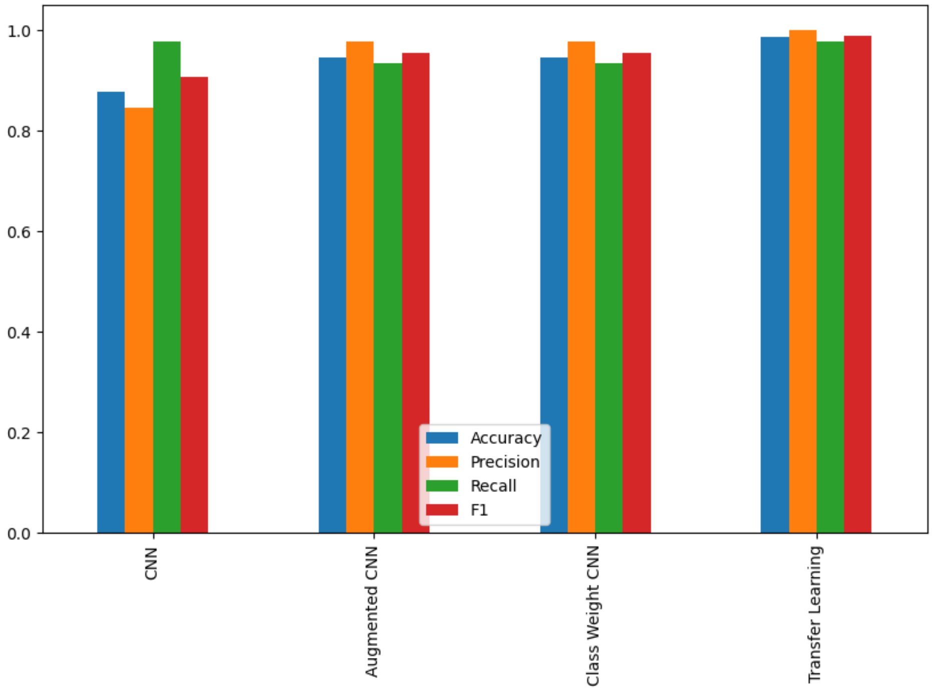

Fig3. Model Comparison graph

While table1 presents the quantitative performance, Fig.3 shows the performance trends of four models using bar graph. The baseline CNN shows imbalance between precision and recall means the model detect all actual positive and also misclassify negative as positive. Augmented CNN gives more stable and balanced results using data augmentation which reduce over fitting and improves model generalization. Similarly Class weight CNN reveals weaker impact on model performance as class imbalance is not the major factor in this dataset. Transfer learning achieved highest accuracy indicating that model extract important features from data and deliver more generalized results.

4.2 Accuracy graph analysis:

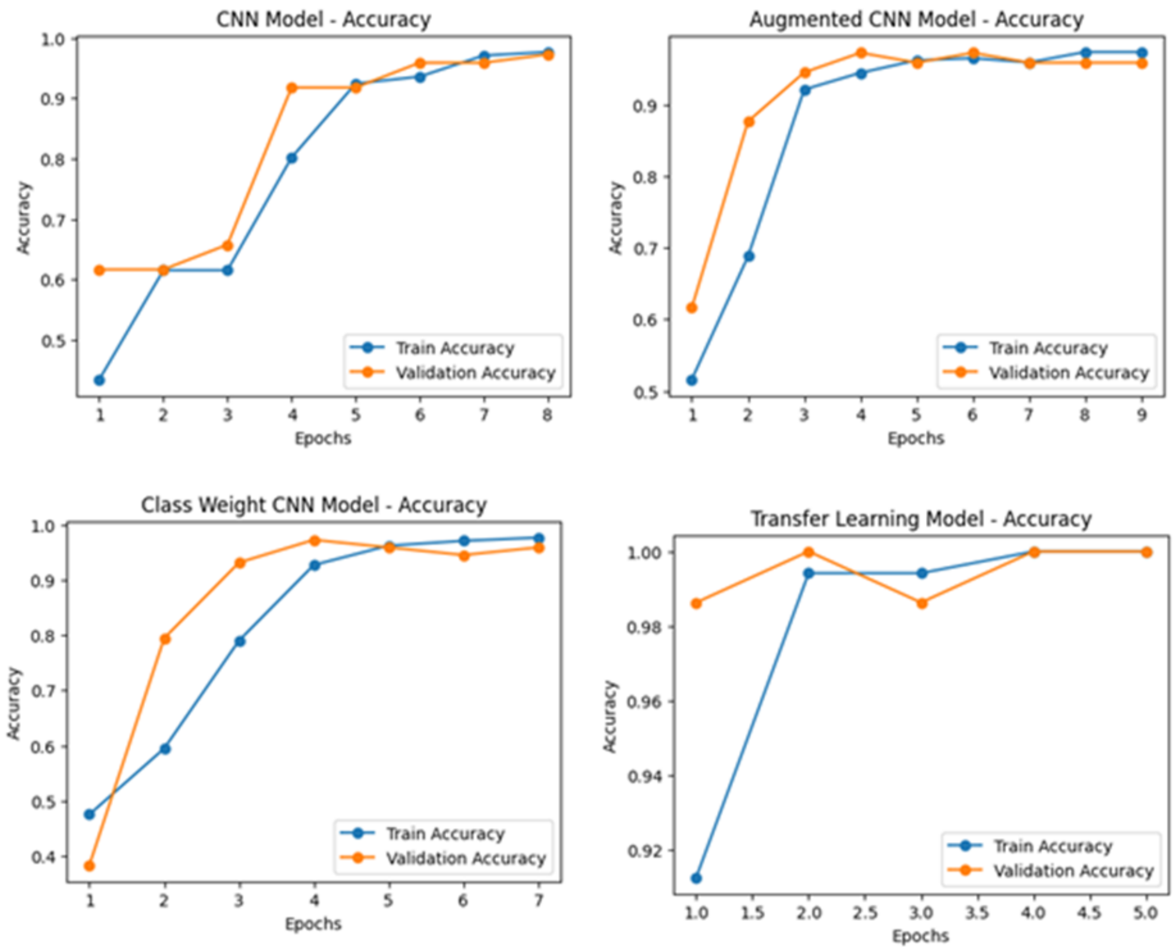

Fig.4 Accuracy vs. Epoch graph analysis

Accuracy graph shows the learning behaviour of all the four models across epochs on training and validation data. In case of simple baseline CNN model, accuracy gradually increase which means model take time to learn patterns from images. The gap between training and validation accuracy indicates that the model takes time to be stable. Augmented CNN achieved high validation accuracy which indicates better generalization and reduce over fitting due to the variation in data. Class Weight CNN got validation accuracy similar to augmented model but it shows slight instability due to handling class imbalance. It doesn't provide significant improvement. Transfer learning achieves high and fast accuracy within a few epochs which means pre-trained model already learnt useful features from data so there is no need to learn feature from scratch.

Precision-Recall Curve:

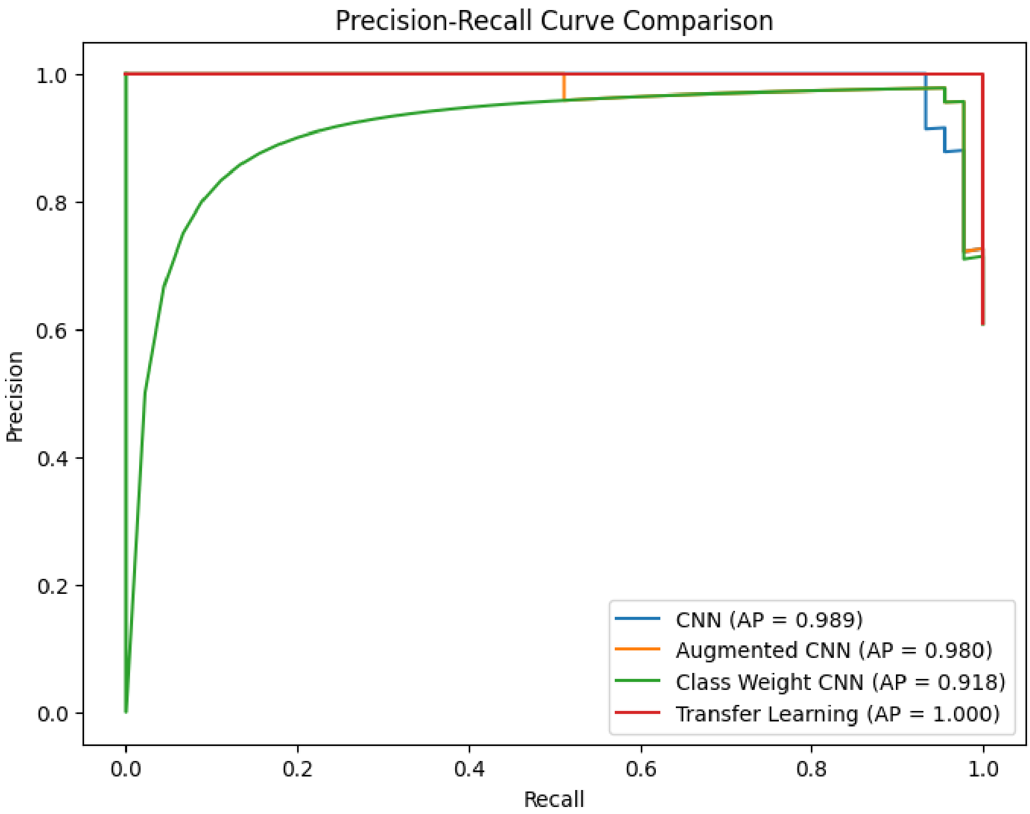

Fig.5 Precision-recall curve analysis

Precision-Recall curve used when the dataset is not balanced. It focuses on positive class. If the curve is on top-right corner it means model achieve high precision and recall by predicting correctly and detect almost all positives[9]. It also shows the stability of the model due to its smoothness. The graph shows that transfer learning got almost perfect balance between precision and recall by achieving highest average precision (AP=1.000) with a smooth curve. It shows the best performance. Baseline CNN and Augmented CNN also perform well with AP values of ~0.989 and ~0.980 respectively and good stability. Class Weight CNN achieved comparatively lower precision (AP~0.918) reflecting while it improves recall by handling class imbalance but it got lower precision. Also it shows some minor zigzag movement in the graph indicating its instability in predictions.

Confusion Matrix Analysis:

Confusion matrix plays important role in evaluating classification problem. There are 29 ring images and 45 necklace images in the test dataset.

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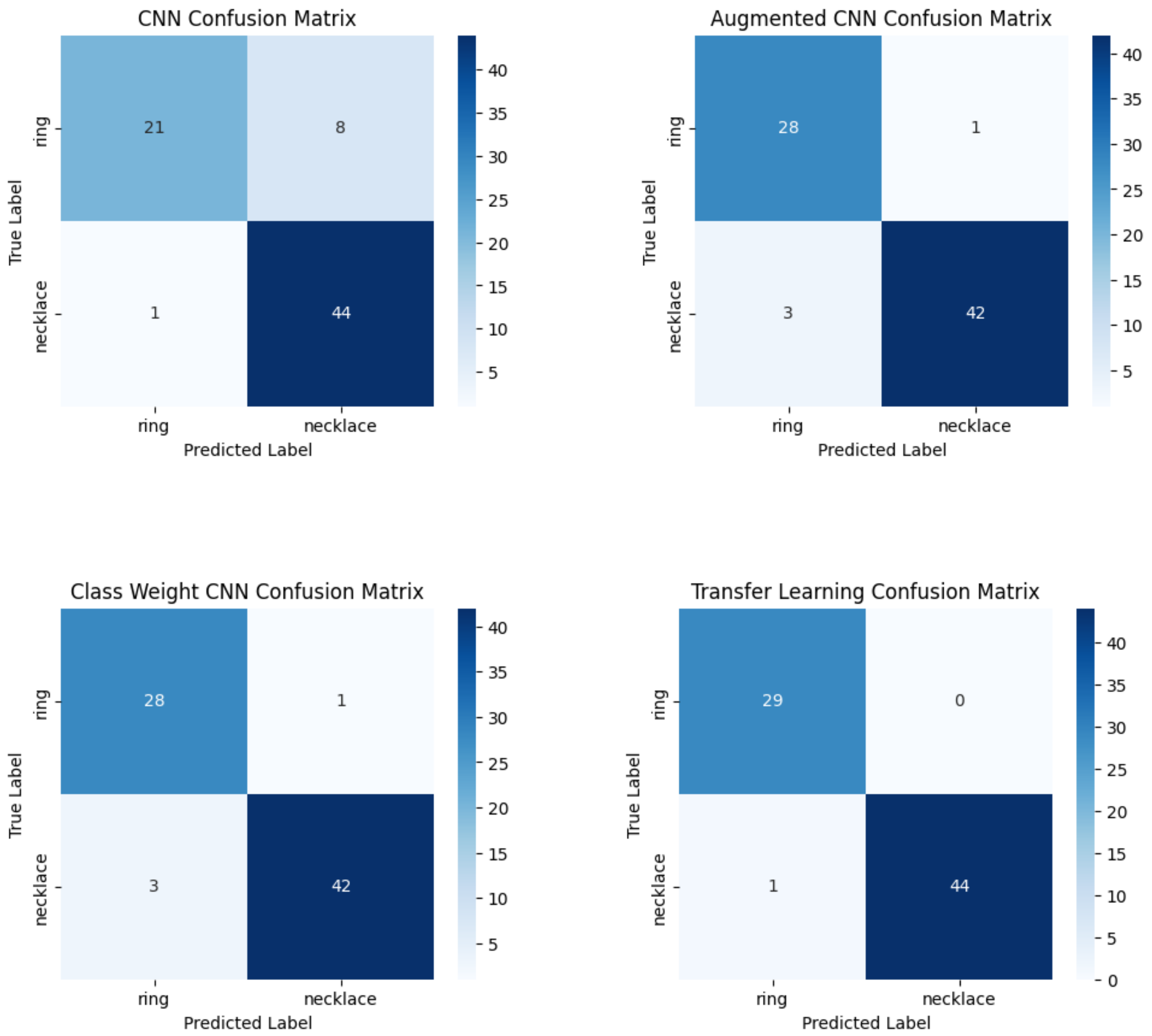

Fig.6 Confusion matrix of four models

Confusion Matrix of CNN model shows that 21 rings were predict correctly and 8 rings are misclassify as necklace, while out of 45 necklaces 44 are predicted correctly and 1 is incorrectly predicted as ring. It means the model is biased towards necklace class. Model struggle in capturing features of ring class. Augmented CNN provides a better generalization due to data enhancement. Only one ring and three necklaces are misclassified. It reduces misclassification compared to baseline model. Class Weight CNN got same result as augmented CNN which shows that class imbalance is not the main problem in this dataset. At last, the transfer Learning (MobileNet) model performs best among all. It predicted all the rings correctly and only one necklace was misclassify as ring. This shows the capability of transfer learning model for extracting important features from data.

Conclusion and Future Work:

In this study, a comparative analysis on jewellery image classification is done by four different models. The accuracy increases from baseline model to transfer learning model. Results are evaluated using different metrics like accuracy, precision-recall curve and confusion matrix. Baseline model give good results but it misclassifies some ring images leading to errors. Augmented CNN provides better results and improve performance by reducing over fitting and increasing accuracy by using data enhancement. Class weight doesn’t provide better results indicating data imbalance is not the main issue. Transfer learning achieved best result among all due to its pre-trained property.

Although, all models achieve good accuracy, but there are also some limitations. The dataset is small and contain only two classes ring and necklace. Only simple approaches were used not any advanced model were used in this work. Also it is not clear how the decisions are made by the model.

In future work, dataset can be extended by adding more classes and more advanced techniques like InceptionV3, Alex Net etc. can be applied on the dataset. Explainable AI techniques can be used to understand the model’s decision making behaviour.

References:

[1] G. Sathiyapriya and S. A. Shanthi, “Image Classification using Convolutional Neural Network,” *2022 1st Int. Conf. Electr. Electron. Inf. Commun. Technol. ICEEICT 2022*, no. May, 2022, doi: 10.1109/ICEEICT53079.2022.9768622.

[2] V. Singh and P. Kaewprapha, “A comparative experiment in classifying jewelry images using convolutional neural networks,” *Sci. Technol. Asia*, vol. 23, no. 4, pp. 7–17, 2018, doi: 10.14456/scitechasia.2018.27.

[3] J. M. Alcalde-Llergo, A. Ruiz-Mezcua, R. Ávila-Ramírez, A. Zingoni, J. Taborri, and E. Yeguas-Bolívar, “Automatic Identification and Description of Jewelry Through Computer Vision and Neural Networks for Translators and Interpreters,” *Appl. Sci. Switz.*, vol. 15, no. 10, pp. 1–16, 2025, doi: 10.3390/app15105538.

[4] B. Chakraborty, R. Mukherjee, and S. Das, “Gemstone Classification Using Deep Convolutional Neural Network,” *J. Inst. Eng. India Ser. B*, vol. 105, no. 4, pp. 773–785, 2024, doi: 10.1007/s40031-024-01003-4.

[5] K. Vaibhav, J. Prasad, and B. Singh, “Convolutional Neural Network for Classification for Indian Jewellery,” *SSRN Electron. J.*, pp. 363–369, 2019, doi: 10.2139/ssrn.3351805.

[6] L. Meng *et al.*, “Deep Learning-Enhanced Jewelry Material Jadeite Jade Quality Assessment,” *Jom*, vol. 77, no. 1, pp. 211–224, 2025, doi: 10.1007/s11837-024-06930-7.

[7] S. Akgül, H. Adin, and H. Ahmetoğlu, “Classification of filigree silver with Artificial Neural Networks according to production methods,” *Eur. J. Tech.*, vol. 14, no. 1, pp. 83–87, 2024, doi: 10.36222/ejt.1336397.

[8] Sapnil Patel, “Tanishq Jewellery Dataset.” [Online]. Available: https://www.kaggle.com/datasets/sapnilpatel/tanishq-jewellery-dataset

[9] J. Miao, S. Brook, and W. Zhu, “(prc) c,” vol. 1, no. 631, pp. 1–19, 2020.