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DEEP LEARNING ARCHITECTURES FOR JEWELLERY IMAGE ANALYSIS

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Abstract :

Jewelry image analysis presents unique challenges due to the fine-grained visual differences, reflective surfaces, spec-ular highlights, and refractive properties inherent in gems and metal ornamentation [1, 11]. These characteristics often confound tra-ditional computer vision methods that rely on handcrafted fea-tures. Deep learning architectures, particularly Convolutional Neu-ral Networks (CNNs) [6, 9] and Vision Transformers (ViTs) [4], have emerged as powerful alternatives capable of capturing both local and global visual patterns. CNNs exploit hierarchical feature extraction through convolutional filters [7, 13], making them effec-tive for capturing local geometric and texture features common in jewelry surfaces [2]. However, CNNs can struggle with global con-textual information in complex scenes and may be sensitive to vari-ations in lighting and reflection patterns. ViTs address this limita-tion by decomposing images into patches and using self-attention mechanisms [8] to model long-range dependencies across an im-age's entire spatial extent [5], facilitating better representation of intricate jewelry details and context [12]. Hybrid CNN-ViT mod-els combine the best of both worlds — CNNs for localized fea-ture learning and ViTs for global context — and show promise in handling reflective and refractive surface variations that tradi-tionally hinder classification and recognition. Recent research in jewelry image recognition has demonstrated the effectiveness of encoder–decoder frameworks for automated description and clas-sification of jewelry items using deep learning — achieving high accuracy in controlled datasets [3]. Furthermore, advances in data preprocessing, including background removal and specular reflec-tion mitigation, significantly improve performance in real-world scenarios [10, 14, 15]. This paper reviews these architectures and methodologies, evaluates their strengths and weaknesses in jewelry image analysis, and outlines future directions, such as the integra-tion of vision language models and contrastive learning, to further enhance accuracy and robustness in reflective and texture-rich vi-sual domains.

Index Terms : Convolutional Neural Networks, Vision Trans-formers, Jewelry Image Analysis, Material Detection, Stone Grad-ing, Edge AI, Augmented Reality.

Introduction :

The jewelry industry occupies a significant position within the global economy, valued at hundreds of billions of dol-lars annually and driving consumer demand across diverse markets including luxury retail, e-commerce, and personal-ized commerce platforms. High-value gemstones and orna-mentation not only represent substantial material worth but also cultural, aesthetic, and emotional significance. Within e-commerce contexts, accurate classification, retrieval, ap-praisal, and description of jewelry images directly influ-ences user experience, search effectiveness, inventory man-agement, and automated catalogue generation [3]. However, the traditional pipeline of jewelry appraisal and image clas-sification remains largely manual, subjective, and labor in-tensive [1]. Expert gemologists and appraisers, while highly skilled, are limited by human constraints: visual fatigue, inter-observer variability, and inconsistency in interpreta-tion, especially when dealing with large inventory scales typical of online marketplaces. Furthermore, manual pro-cessing cannot feasibly support real-time search applications or large catalogues containing millions of images without substantial cost and delay [10].

The intrinsic visual complexity of jewelry imagery — in-cluding fine-grained variations in design, texture, reflective surfaces, and complex optical phenomena such as specu-lar highlights and refraction through gemstones — exac-erbates these challenges [11]. Such visual properties in-crease the difficulty of accurate segmentation, classifica-tion, and description when using classical image analysis techniques dependent on handcrafted features [2]. The ad-vent of deep learning architectures, notably Convolutional Neural Networks (CNNs) [6], [9] and Vision Transformers (ViTs) [4], offers compelling alternatives that can learn hi-erarchical and context-aware representations directly from raw pixel data. CNNs have demonstrated formidable perfor-mance across traditional image classification problems and fine-grained tasks [7], [13], while ViTs extend this by en-abling global context encoding through self-attention mech-anisms [8], [5]. Adopting deep learning approaches for jew-elry image analysis promises not only higher classification accuracy but also scalable, robust solutions capable of han-dling real-world variations in lighting, orientation, and sur-face properties which remain problematic for classical meth-ods [12], [15].

Literature review :

More advanced deep learning frameworks extend CNNs by combining them with sequence modeling or caption gener-ation techniques. Work by Alcalde-Llergo et al. on jew-elry recognition via encoder-decoder models [3] uses neural networks to generate natural language descriptions of jew-elry images, capturing details like type, color, and material. By simulating expert human description, these systems pro-vide richer semantic understanding beyond simple classifi-cation, with reported captioning accuracy exceeding 95 on curated accessory datasets. Such models demonstrate the potential for deep learning not only to classify but also to describe jewelry content [3], an important capability for in-ventory indexing, search assistance, and virtual assistants in e-commerce.

While CNNs excel at capturing local hierarchical features [9], they may not natively encode global context — particu-larly relevant when discriminating subtle design differences or reflective patterns across an entire jewelry item. This limitation motivates the exploration of Vision Transformers (ViTs) [4], which leverage self-attention mechanisms origi-nally developed for natural language processing [8] to model long-range dependencies across image patches [5]. A ViT divides an image into a sequence of non-overlapping patches and processes them akin to tokens in a language model, capturing global interactions and context that may elude purely convolutional architectures. Studies on ViT archi-tectures have shown competitive or superior performance to CNNs on large-scale image classification benchmarks, par-ticularly where global context enhances discrimination [12]. Consequently, emerging research in visual fine-grained do-mains like jewelry analysis explores hybrid CNN–ViT mod-els that combine local feature learning with global attention to achieve robust representation of both fine detail and over-all structure.

Beyond classification, recent research also explores inte-grating transformer and captioning models to generate se-mantic descriptions and metadata for jewelry images, further enabling advanced downstream tasks such as search, recom-mendation, and automated tagging in e-commerce platforms — all critical to scalable operation and personalization in commercial settings [14].

Deep learning methods overcome these limitations. CNNs automatically extract hierarchical features from raw images, capturing edge, texture, and semantic patterns [7]. ResNet [6] and EfficientNet [13] architectures have demon-strated superior performance in gemstone classification and material detection [2]. Encoder-decoder models, as shown by Alcalde-Llergo et al., generate descriptive captions for jewelry, providing semantic metadata alongside classifica-tion [3]. Vision Transformers further enhance performance by modeling global relationships between image patches [5], enabling the detection of tiny inclusions and subtle design variations that are often missed by standard CNNs.

Hybrid CNN–ViT models have emerged as effective so-lutions for fine-grained jewelry analysis [11]. CNN layers extract local features, which are then processed by ViTs to encode global context. This combination improves accu-racy for tasks such as diamond grading and gemstone clas-sification [1], while preprocessing pipelines and advanced object detection frameworks like YOLO [15] and Faster R-CNN [10] mitigate challenges from glare, specular reflec-tion, and background clutter.

Methodology :

The proposed framework for jewelry image analysis inte-grates advanced preprocessing techniques, deep learning ar-chitectures, and domain-specific evaluation strategies. The methodology is designed to handle the unique visual chal-lenges of jewelry imagery [1], including reflective metal-lic surfaces, gemstone refraction, intricate design patterns, and high intra-class similarity [11]. The workflow is divided into three primary stages: data preprocessing, model train-ing (CNN and ViT architectures), and task-specific evalua-tion (material detection and stone grading).

A. Data Collection and Dataset Preparation :

High-quality jewelry images were collected from multiple sources, including e-commerce platforms, curated accessory datasets [3], and specialized gemstone image repositories [1, 2]. Images encompassed diverse categories such as rings, necklaces, earrings, and bracelets, captured under controlled and uncontrolled lighting conditions [14]. The dataset was annotated for multiple attributes:

- Category labels: ring, necklace, bracelet, earrings.
- Material labels: gold, silver, platinum.
- Gemstone properties: type, cut, clarity, color, and carat weight [1].
- Quality labels: based on the 4 Cs (Cut, Color, Clarity, Carat).

To facilitate robust evaluation, the dataset was divided into training (70%), validation (15%), and testing (15%) sets while maintaining class balance and diverse lighting conditions.

B. Image Preprocessing :

Jewelry images often contain glare, specular highlights, re-flections, and complex backgrounds. Preprocessing aims to standardize inputs and enhance model performance [14].

1. Background Removal :

Semantic segmentation: Pre-trained models and region-based detection frameworks [10] were used to isolate jew-elry objects from heterogeneous backgrounds while preserv-ing fine edges.Mask refinement: Morphological operations and Conditional Random Fields (CRFs) were applied to im-prove boundary consistency and remove residual noise.

2. Glare and Reflection Handling :

Specular highlight mitigation: Images were converted to HSV and LAB color spaces to identify high-intensity glare regions. Adaptive inpainting and reflection removal fil-ters were applied to address the challenges noted in gem-stone computer vision [1].Polarization simulation: Syn-thetic data augmentation using polarization-inspired trans-formations was employed to improve robustness against re-flective surfaces.

3. Data Augmentation :

To improve generalization and address intra-class variabil-ity, the following augmentation techniques were applied, consistent with modern deep learning practices [9, 15]:

- Random rotations and horizontal/vertical flips.
- Brightness, contrast, and color jittering.
- Zooming and random cropping for close-up gemstone analysis.

4. Normalization and Resizing :

All images were resized to 224 × 224 pixels to match CNN and Vision Transformer (ViT) input requirements [4, 6]. Pixel values were normalized using ImageNet mean and standard deviation values to enable effective transfer learn-ing.

C. CNN-based Feature Extraction :

Convolutional Neural Networks (CNNs) were employed for hierarchical feature extraction. The following architectures were used:

- ResNet-50 [6]
- EfficientNet-B3 [13]

These networks capture fine-grained texture, edge infor-mation, and design patterns essential for identifying metal types and gemstone features [7, 11]. Transfer learning from ImageNet-pretrained weights enabled faster conver-gence and improved performance on jewelry-specific visual domains [9].Early convolutional layers detect edges and gra-dients, intermediate layers capture surface textures such as brushed metals and gemstone facets, and deeper layers en-code high-level semantic representations of jewelry items. Although CNNs excel at local feature extraction, they are limited in modeling long-range dependencies, particularly for detecting small inclusions within gemstones.

D. Vision Transformers for Global Context :

Vision Transformers (ViTs) utilize self-attention mecha-nisms [8] to model long-range dependencies across image patches. Images are divided into fixed-size patches (e.g., 16 × 16), which are treated as tokens in a transformer ar-chitecture [4].ViTs enable:

- Fine-grained inclusion detection through attention across gemstone regions [12].
- Global context modeling for overall jewelry design and symmetry [5].

Hybrid CNN-ViT architectures combine CNN-based lo-cal feature extraction with transformer-based global reason-ing [5, 12]. This hybrid approach is particularly effective for diamond clarity and cut assessment, where both local tex-tures and global symmetry are important.

E. Material Detection :

Material classification distinguishes between gold, sil-ver, and platinum jewelry.Feature extraction: CNN and ViT models encode color distribution, reflectance patterns, and surface texture using RGB and LAB color spaces [11].Training strategy: ImageNet-pretrained models were fine-tuned on labeled jewelry datasets.Classification head: Fully connected layers with softmax activation predict mate-rial categories.Evaluation metrics: Accuracy, precision, re-call, and F1-score were used, along with cross-validation to reduce dataset bias [2].CNNs capture localized metallic tex-tures, while ViTs improve robustness under complex light-ing and reflection conditions .

F. Stone Grading Based on the 4 Cs :

Gemstone grading was performed based on Cut, Color, Clar-ity, and Carat [1].

- **Cut :** ViTs model global symmetry and facet alignment[12]; CNNs capture local edge structures.

- **Color :** Pixel distributions in HSV and LAB color spaces capture subtle tint variations [2].
- **Clarity :** High-resolution patches enable detection of tiny inclusions using self-attention [4, 5].
- **Carat :** Estimated using geometric scaling after seg-mentation [10, 15] and depth approximation.

Synthetic inclusion insertion and glare simulation were used to enhance robustness for clarity detection. Multi-task learning was adopted, allowing a single network to predict multiple grading attributes simultaneously [3].

G. Training and Optimization :

Loss functions: Cross-entropy loss was used for classifi-cation tasks, while Mean Squared Error (MSE) was used for continuous predictions such as carat weight.Optimizer: AdamW optimizer with learning rate scheduling and weight decay was employed, following established transformer optimization strategies [8].Regularization: Dropout, data augmentation, and early stopping based on validation loss were used to prevent overfitting. Transfer learning from ImageNet significantly reduced training time and improved generalization [6, 13].

Analysis :

The performance of Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) was evaluated us-ing high-resolution jewelry image datasets under multiple real-world conditions [1], including varying illumination, background complexity, and reflective surfaces [11].

A. Evaluation Metrics :

The following evaluation metrics were used to assess model performance, following standard protocols for fine-grained image recognition [11, 12]:

- **Accuracy :** Overall correctness of classification.
- **Precision and Recall :** Particularly important for iden-tifying rare gemstone defects or inclusions [1].
- **F1-score :** Harmonic mean of precision and recall, suit-able for imbalanced class distributions [2].
- **Top-k Accuracy :** Applied to multi-class tasks such as gemstone type classification [9].

B. CNN vs. ViT Performance

C. CNN vs. ViT Performance

Table 1 compares the performance of ResNet-50 [6] and ViT models [4] across key jewelry analysis tasks.

Table 1: Comparison of CNN and ViT Performance

Task	ResNet-50	ViT	Observations
Material Detec-tion	94.2%	96.8 %	ViT handles com-plex reflecti ons better [12].
Inclusion De-tection	82.5%	91.7 %	Global context en-ables detection of tiny inclusions [5].
Stone Grading (4 Cs)	88.1%	93.4 %	Hybrid CNN–ViT model achieves high-est precision [3].

Key observations include:

- CNNs excel at local feature extraction such as textures and fine-scale patterns [7, 13] but may miss broader contextual information.
- ViTs leverage self-attention [8] to perform holistic analysis of gemstone surfaces, capturing relationships between fine-grained patches [4].
- Hybrid CNN–ViT architectures combine local sensitiv-ity with global reasoning [5], resulting in superior per-formance for inclusion detection and grading tasks.

D. Impact of Preprocessing :

Preprocessing techniques had a significant impact on model performance, consistent with findings in automated jewelry description [3]:

- Glare mitigation improved material classification accu-racy by approximately 3–5% and inclusion detection accuracy by nearly 6% [1].
- Background removal using modern detection frame-works [10] reduced false positives in material detection and stone grading, particularly in cluttered e-commerce images [14].
- Data augmentation techniques such as color jittering, rotation, and zooming [9, 15] mitigated overfitting and enhanced generalization to unseen lighting conditions and camera angles.

E. Transfer Learning Effectiveness :

Transfer learning proved highly effective in jewelry image analysis, as observed in recent gemstone classification stud-ies [2]:

- Fine-tuning ImageNet-pretrained models [6, 9] reduced convergence time by approximately 40% compared to training from scratch.

- Pre-trained models encode fundamental visual features such as edges and textures [7] that transfer well to re-flective metals and gemstone surfaces.
- Multi-task learning with shared CNN–ViT backbones enabled simultaneous prediction of material composi-tion and 4C attributes [3], improving computational ef-ficiency.

F. Real-World Application Insights :

The comparative analysis provides insights for practical de-ployment:

- ViTs demonstrate strong potential for automated dia-mond certification and virtual appraisal systems due to their ability to detect subtle inclusions [12].
- CNNs remain suitable for high-throughput applications such as basic material classification [13], particularly when computational resources are limited.
- Hybrid CNN–ViT models offer the best trade-off be-tween accuracy and contextual understanding for pre-mium applications [5].

G. Limitations and Considerations :

Despite promising results, several limitations remain:

- **Dataset scarcity :** High-quality labeled datasets for gemstone inclusions are limited [1]. Synthetic data augmentation partially alleviates this issue.
- **Hardware requirements :** ViTs require greater com-putational resources than standard CNNs [4], necessi-tating a balance between accuracy and inference speed.
- **Specular variability :** Extreme reflections and gem-stone translucency can still lead to misclassification [11]. Future work includes integrating vision-language models and contrastive learning to further enhance ro-bustness.

Discussion and Future Directions :

The integration of deep learning architectures into jewelry image analysis has demonstrated significant improvements over traditional approaches, particularly in classification, material detection, and gemstone grading. Beyond labora-tory and server-based environments, emerging solutions in-creasingly leverage Edge AI, Augmented Reality (AR), and ethical AI frameworks to enhance consumer experience and industry standards.

A. Edge AI for Mobile Jewelry Recognition :

Edge AI refers to deploying machine learning models di-rectly on end-user devices, such as smartphones and tablets, rather than relying exclusively on cloud-based computation. The adoption of Edge AI for jewelry recognition offers sev-eral advantages:

- **Instant Appraisal :** Lightweight CNNs and compact Vision Transformer (ViT) models enable near real-time on-device assessment of jewelry materials, gemstone types, and preliminary 4C grading, reducing depen-dence on expert appraisers.
- **Privacy and Data Security :** Local image processing eliminates the need to transmit

sensitive visual data to remote servers, addressing growing consumer concerns regarding privacy.

- **Low Latency and Offline Operation :** Edge AI sup-ports immediate feedback without network depen-dency, making it suitable for regions with limited con-nectivity and high-end retail environments.

Recent advances in model quantization, pruning, and knowledge distillation have enabled the deployment of com-putationally intensive architectures such as ViTs on mobile devices. Hybrid CNN–ViT models can be optimized for ARM-based processors while preserving accuracy in detect-ing subtle gemstone inclusions. Furthermore, edge deploy-ment facilitates incremental on-device learning, allowing models to adapt to user-specific contexts and camera char-acteristics.

B. Augmented Reality and Virtual Try-On Applications :

Augmented Reality (AR), when combined with deep learn-ing, has transformed online jewelry retail by overcoming limitations of static imagery. AR-based Virtual Try-On (VTO) systems enable immersive and interactive user ex-periences:

- **Deep Learning-Enhanced Fit and Placement :** CNNs and ViTs segment the user's hand, wrist, or neck from live video streams and overlay jewelry with accurate orientation and scale. ViT self-attention mechanisms capture spatial relationships for realistic alignment.
- **Dynamic Lighting and Material Simulation :** Prepro-cessing pipelines that account for glare, reflection, and metal properties allow realistic rendering of jewelry un-der varying lighting conditions.
- **User Engagement and Conversion :** AR-driven try-on experiences increase consumer confidence, reduce re-turn rates, and encourage higher-value purchases com-pared to conventional e-commerce interfaces.

The integration of Edge AI with AR enables real-time vir-tual try-on without reliance on cloud infrastructure. Future work may incorporate generative models to simulate inter-actions between jewelry, skin tones, clothing textures, and ambient lighting for personalized visualization.

C. Ethical Considerations and Counterfeit Detection :

As AI increasingly influences consumer decisions and re-tail operations, ethical considerations related to authentic-ity, sustainability, and consumer protection become critical. One significant application is the differentiation between natural and lab-grown gemstones:

- **Automatic Counterfeit Detection :** High-resolution imaging combined with CNN and ViT architectures enables detection of micro-inclusions, facet symmetry irregularities, and optical anomalies characteristic of synthetic stones.
- **Sustainability and Consumer Trust :** AI-driven ap-praisal promotes transparent sourcing and adherence to international gemological standards. Integrating deep

learning with blockchain technology can ensure tamper-proof provenance tracking.

- **Regulatory Compliance :** Automated identification tools assist regulatory agencies in monitoring trade practices and enforcing consumer protection laws.

These ethical applications require carefully curated train-ing datasets to avoid bias and overconfidence. Future re-search should explore multimodal learning frameworks that combine visual, spectral, and provenance metadata for ro-bust and fair authentication systems.

D. Future Directions :

Future research in jewelry image analysis using deep learn-ing is expected to focus on the following directions:

- Hybrid Multi-Modal Architectures: Integrating CNNs, ViTs, and transformer-based encoder–decoder models with spectral and near-infrared imaging for en-hanced grading and counterfeit detection.
- Personalized Edge Applications: On-device learning and lightweight architectures to deliver personalized appraisal and virtual try-on experiences.
- AI-Augmented Expertise: Positioning AI as a decision-support tool that complements, rather than re-places, human experts in final valuation and certifica-tion.
- Retail Ecosystem Integration: Seamless integration of AI-powered recognition, AR-based shopping, inven-tory management, and blockchain verification for trust-worthy and engaging consumer experiences.

In summary, the convergence of Edge AI, Augmented Reality, and ethical deep learning frameworks represents a transformative frontier in jewelry image analysis. Contin-ued advancements in CNNs, Vision Transformers, and hy-brid models will enable scalable, real-time, and trustworthy solutions that augment expert appraisal and redefine digital jewelry retail.

Conclusion :

This research presented a comprehensive study of deep learning architectures for jewelry image analysis, addressing key challenges such as reflective surfaces, complex back-grounds, and fine-grained gemstone details. Traditional computer vision techniques, which rely on handcrafted fea-tures, were found to be inadequate for handling the high intra-class similarity and optical distortions inherent in jew-elry images. In contrast, deep learning models demonstrated superior robustness and scalability.

Convolutional Neural Networks (CNNs) proved effective in extracting local texture and material-based features, mak-ing them suitable for tasks such as jewelry category classi-fication and material detection. Vision Transformers (ViTs), leveraging self-attention mechanisms, showed enhanced ca-pability in capturing global contextual relationships and de-tecting subtle gemstone inclusions, which are critical for ac-curate stone grading and quality assessment. The integration of advanced preprocessing techniques, including glare sup-pression and background removal, further improved model performance.

The study also highlighted practical applications of deep learning in real-world scenarios such as automated appraisal, e-commerce product tagging, virtual try-on systems, and counterfeit detection. Emerging trends like Edge AI and augmented reality indicate a shift toward real-time, user-centric jewelry analysis systems. Overall, the findings con-firm that hybrid deep learning frameworks combining CNNs and Vision Transformers offer a promising direction for re-liable, scalable, and ethical jewelry image analysis, paving the way for future innovations in intelligent luxury retail sys-tems.

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