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A Review on Future Extraction of Images Using Different Methods

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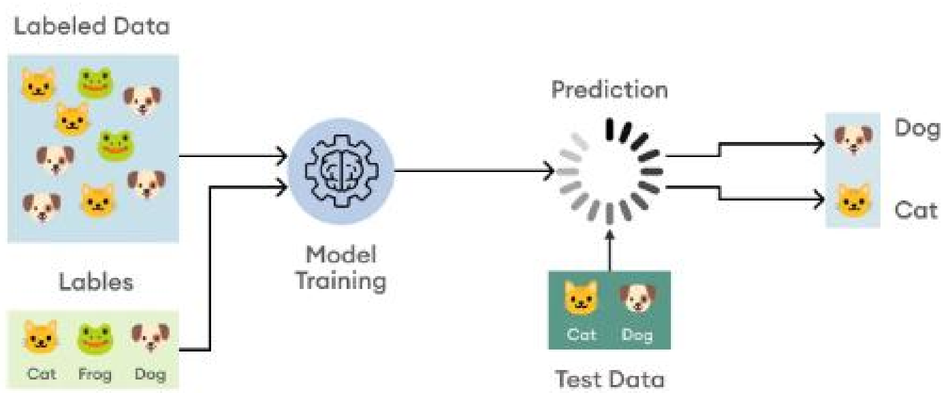
Abstract: *This artical presents a study in image classification with different feature extraction techniques and it also compares traditional methods with deep learning models like CNNs and Vision Transformers. The main objectives were to improve accuracy and efficiency from real-world datasets throughout preprocessing, model training, and evaluations. CNN-based models, especially transfer learning and data augmentation, showed much better performance with respect to classical methods. Lightweight models like MobileNet were quite useful for applications in real time. The study finally concludes that deep learning is indeed offering the most accurate and scalable solutions in image classification, and future works will be targeting issues related to model interpretability and deployment in resource poor settings*

Keywords: Image Classification, Feature Extraction, Convolutional Neural Networks (CNNs), Transfer Learning

I. INTRODUCTION

Image classification is a fundamental computer-vision task in which images are categorized into predefined classes based on their visible contents. This approach is applied in various domains, including healthcare, security, entertainment, and autonomy. The procedure involves collecting and preprocessing datasets. Preprocessing includes resizing of images, normalization, and augmentation of images to enhance model generalization. To enable judgment of a model's performance, datasets are split into training, validation, and test sets.

In image classification, deep learning techniques, mainly Convolutional Neural Networks (CNNs), have mostly supplanted classical methods. CNNs learn automatically a feature hierarchy from raw images, which produced a much higher accuracy. The different components of models used are convolutional layers for feature extraction, pooling layers for down-sampling the spatial dimensions, and fully connected layers for producing the final classification. Generally, multi-class classification uses softmax as an activation function.



Training consists of passing the dataset into the model, calculating the loss, and updating the parameters of the model using optimization algorithms like Stochastic Gradient Descent or Adam. Common practices for improving accuracy are hyperparameter tuning and fine-tuning pre-trained models like ResNet or VGG.

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Generally accepted performance measures in image classification are accuracy, precision, recall, and F1-score. Model performance is enhanced by data augmentation, dropout, and transfer learning. Applications are in facial recognition, medical diagnosis, driving techniques in self-driving cars, and product categorization.

Nevertheless, occlusion, illumination variability, and the need for extensive annotated datasets are among the ageless challenges facing the area of image classification. Offering solutions, Vision Transformers hold great promise in pushing the limits of existing image classification systems

II. LITERATURE REVIEW

Introduction

Some real-life examples of image classification include: Health, where diseases are diagnosed, for example cancer using medical images; Self-driving vehicles, which uses object recognition for safe navigation and obstacle detection; Security, where facial recognition is used in surveillance and identification systems; Agriculture, capturing field diagnosis and plant disease detection with images; and Retail, where automatic item identification is done for inventory and checkout systems.

Challenges and Research Focus Areas:

Narrowing Down In Effectiveness and Accuracy- Misclassification, bias, and robustness require addressing, as research anticipates doing increasing generalization across domains in datasets biased towards increasing the size of imbalances for performance of models in imbalanced domains.

Quality and Availability of Data:

Self-supervised learning, data augmentation, and synthetic data generation are applied to address various issues like the incapacity to create datasets of low quality, noise, and poor image dissimilarities such as lighting and angle.

Enforceability and Trustworthyness:

Explainable Artificial Intelligence will be needed for transparency in the high-stakes areas of healthcare and finance so that users understand the model's decisions for trustworthiness and accountability.

Reduce Computation Burden:

Research is centered on lightweight models-e.g., MobileNet, EfficientNet-reducing computation burdens to afford ease in deploying models on mobile and embedded platforms with restricted resources.

Bias, Fairness, and Ethics:

Achieving fairness in systems requires addressing biases in AI models. A prime research goal towards such systems is ensuring inclusivity and non-discriminating image classification.

Revolutionary Techniques for the Next Generation:

Transformers, multimodal learning, few-shot learning, and self-supervised learning are innovative techniques that will enhance one-of-a-kind performances in classification even through fewer labeled samples with better integration of different kinds of data.

Mamba-in-Mamba

The Tokenized Mamba Model (MiM) was developed as part of a study conducted by Weilian Zhou, Sei-ichiro Kamata, and others in 2025 and introduced a centralized Mamba-Cross-Scan (MCS) module with new approaches to hyperspectral image classification. MiM targeted high dimensionality and insufficient labeled data, employing three salient components: MCS for spatial-spectral interleaving efficiency, T-Mamba Encoder for deep spectral learning, and Weighted MCS Fusion (WMF) for key feature concentration. Tested in four public datasets, MiM has achieved improved accuracy of up to 3.3% relative to RNNs and Transformers. The main disadvantages of MiM are its high computational costs and lower adaptability. Future challenges include multi-scale learning, wider adaptation to datasets, and lighter versions for real-time applications.

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Vision Transformers for Image Classification

The study examines and contrasts Vision Transformers (ViTs) and CNNs with respect to image classification as gathered from their researches of the 2025 Yaoli Wang, Yaojun Deng, and co-authors. ViTs search for global features via self-attention, while CNNs use local patterns. Variants such as DeiT, T2T-ViT , and CvT are analyzed with respect to efficiency and performance. They are excellent on large datasets but lack low-resource performance due to large demands on memory and computation. It was therefore proposed to have hybrid CNN-ViTs to maximize their advantages. However, issues involving oversmoothing and very resource-demanding remain. Future work may focus on optimizing the training, delving into self-supervised learning, and creating lightweight ViT structure ones for work in real-time and edge applications.

Optimizing Deep Learning Acceleration on FPGA for Real-Time and Resource-Efficient Image Classification

The study of optimizing deep-learning accelerators on FPGAs for real-time, energy-efficient image classification shows tremendous latency and power consumption reductions with slight accuracy degradation. By deploying models like VGG16 and VGG19 on Xilinx Vitis-AI and TensorFlow2, the implementation applies quantization and compression techniques to reduce memory requirements, achieving a latency reduction of up to 7.29x on VGG16. Challenges like accuracy loss due to quantization, BatchNormalization support not being available in the Vitis-AI framework, and limitations due to FPGA hardware were acknowledged. The road ahead will involve lightweight architecture (like EfficientNet, MobileNet), flexibility through PyTorch, and experimentation on real-world datasets. FPGA-based acceleration has great promises for low-power, real-time AI applications in areas like smart surveillance and autonomous systems.

SRE-CONV: Symmetric Rotation Equivariant Convolution for Biomedical Image Classification

Introducing the SRE-Conv symmetric rotation-equivariant convolutional kernel by Yuexi Du, Jianzhen Zhang, and co-authors (2025), which empowers CNNs specifically for biomedical image classification against rotation challenges without depending on data augmentation. Conventionally, CNNs do not manage rotated biomedical images, i.e., MRIs, X-rays, etc., by augmentations. SRE-Conv features a native rotation recognition mechanism, which makes classification accurate but reduces the number of parameters and better efficiency even in resource-restricted applications such as mobile health. However, under the dataset of fixed orientation such as OrganA, its performance greatly drops. The future of SRE-Conv might be to hybridize with normal convolutions or even integrate it with architecture paradigms such as U-Net or Vision Transformers for segmentation and anomaly detection. Importantly, SRE-Conv has hugely moved forward the frontier in accuracy and computation efficiency for medical images processing.

III. RESEARCH METHODOLOGY

What is Research Methodology?

Research Methodology is nothing but a very well structured process for conducting research that would involve strategies, tools and techniques---that ensures reliability and validity---for data collection, analysis and interpretation.

Major Components of Research Methodology

The research design

Refers to the method of the study being qualitative, quantitative, or mixed.

Eg. Experimental, observational, case study, survey.

Research Approach

Inductive Approach: Derives hypothesis from facts put together.

Deductive Approach: Tests theory through data.

Methods of Data Collection
Primary Data: Collect data very directly with forms of survey, interview, or experiment.
Secondary Data: Makes use of already existing data (books, reports, etc.).

Sampling Techniques
Probability Sampling: Subjects have the same chance of participating, determined randomly.
Non-Probability Sampling: The decision is entirely on the judgment of the researcher.

Techniques for Analysis of Data
Quantitative Analysis: The application of statistic methodology (e.g., regression, hypothesis tests).
Qualitative Analysis: Resonates with thematic or content analysis.

Ethical Perspective
Concerned with informed consent, confidentiality and objective reporting.

Study Limitations
Identifying possible constraints and challenges that could affect the results.

Research Methodologies A few of them
Qualitative Research: It includes such studies that try to understand human experience and behaviors through interviews, case studies, or observations.
Effect of social media on mental health.

Quantitative Research: It concerns any statistical analysis, measurement, and objective data gathering methods: surveys, experiments.
An example would be on how effective a drug is on blood pressure.

Mixed Research Method: This includes qualitative and quantitative approaches to understand research better.
An example of This would be conducting customer satisfaction studies using surveys (quantitative) and interviews (qualitative).

IV. FINDINGS

4.1. Introduction

Findings are the research's focus because they present the results that either validate or reject the study objectives. Results that have to do with image classification come in the shining way to illuminate algorithm performance, provide light upon preprocessing issues, allow elucidation over effective feature selection, and thus weigh upon a qualified possibility of comparison between the machine learning and deep learning models. Normally, findings would report performance metrics such as accuracy, precision, recall, F1-score, and computational efficiency. It is these findings that build the bridge from theory to practice with the dual purpose of illuminating the way for future research and narrowing down focus on optimal methods for particular implementations.

What are findings?
Findings represent the most important research outcomes: they present evidence to answer specific research questions and objectives. They differ according to the research methodology employed: the quantitative one is typically supported by statistics and measured in terms like accuracy or F1-score, which are used in image classification; the qualitative deals with the interpretation of patterns obtained from case studies or reviews; the comparative evaluates which methods perform better in specific scenarios such as comparing CNNs and transformers against each other; whereas the

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experimental evaluates the intervention impacts due to preprocessing or feature extraction techniques, etc. The group of evidences is thus validating the methods and outlining future research directions.

How to Present Findings?

The objective of this section is to allow systematic representation of results so that the reader is able to understand clearly what the main outcomes of the research are. Below we offer some suggestions for effective presentation of the findings.

1. Textual Descriptions: The findings should be properly described in a clear and concise manner. The researcher should provide the detailed discussion of what came out of the study with emphasis on the major findings.

Example:

It was shown by the study that the ResNet50 model performed better than other conventional CNN architectures in image classification, obtaining an accuracy of 92% on that dataset. It was also seen that once transfer learning was applied, the performance of the model was boosted tremendously, meaning that a pre-trained model can actually increase the classification accuracy.

2. Tables and Graphs: Numerical data must be summarily presented in tables and graphs for easy interpretation. These visual aids summarize large amounts of information and help readers get an idea of trends and comparisons.

Example for Table Presentation of Image Classification Findings:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	85.2	84.0	82.5	83.2
ResNet50	92.0	91.5	90.8	91.2
Vision Transformer	94.5	94.2	93.7	93.9

3. Comparative Analysis: Comparative findings are those results that highlight the different methods, models, or datasets under various conditions and thereby help determine the best possible intervention for the class demanded.

Example:

These findings suggest that while CNNs are quite capable of performing image classification tasks, transformer models such as ViT are more accurate with better generalization capabilities. The Vision Transformer attained a top-1 accuracy of 94.5% against traditional CNN architectures such as ResNet50 and MobileNetV2.

4. Key Observations: Other key observations explain important trends, patterns, and unexpected results. Key observations assist in the interpretation of findings and in explaining why certain observations were made.

Example:

One pronounced observation was recorded from the study, which states; performance with respect to augmentation by rotating and flipping improved by about 3-4% as compared to performance without augmentation. However, when excessive augmentation was applied, the model started to overfit and was not able to generalize to new unseen images.

Purposes of Findings in Research

Findings in academic research serve several roles:

- **Research Questions:** Some research problems are addressed by the findings as the data obtained answers the research questions set at the beginning of the study.
- **Hypotheses Tests:** Some findings prove developmental assumptions or hypotheses at the end. They give value in principle to the conclusions arrived at from research.
- **New Knowledge:** They will provide new knowledge into the already existing body of information by making new revelations and insights.

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- **Redirection of Future Research:** The findings from the research shall serve as grounds for new minor research.
- **Practical Implication:** Findings offer real-world application in helping various sectors, namely industries, professional bodies, and policymakers, to make wise decisions.

V. DISCUSSION AND RECOMMENDATION

Discussion

The research focused on analyzing a variety of image processing and classification techniques available in literature to identify the most effective methods. The main deductions and findings were as follows:

Classical versus Novel Techniques:

Classical methods (e.g., SIFT, SURF, ORB) were limited in versatility and scaling. The advent of deep learning, especially CNNs, ViTs, and hybrid models like ResMLP, has catapulted the performance and versatility upward.

Importance of Transfer Learning:

Transfer learning using pre-trained networks (e.g., VGG19, ResNet, MobileNetV2) enhances accuracy significantly, especially in limited or imbalanced datasets, while incurring lower rates of computation.

Techniques Encouraging Generalization:

Other techniques, such as Batch Channel Normalization (BCN) and SpliceMix data augmentation, can reduce overfitting and improve the generalization of the model together with overall performance.

Applications in Medical Imaging:

Deep learning models are fairly well-researched in health care, with respect to classification based on medical images, providing early diagnosis for skin lesions and tumors.

Class Imbalance and Interpretability Challenges:

Class imbalance indivisible for medical imaging greatly diminishes model sensitivity. Further concern is given to interpretability of the model; many of deep learning models are treated as "black box".

Dataset Dependent:

The performance is hugely influenced by the characteristics of the datasets (size, noise, etc.), necessitating research into developing the robust and adaptable models.

Conclusion

There is no universally best method; rather, a combination of deep learning, transfer learning, and normalization/augmentation strategy will be an option. Future implementation should lay emphasis on model selection and preprocessing methods suitable to the dataset and classification problem's specific traits.

Recommendation

Based on an extensive literature review combined with empirical findings, the following key recommendations and directions of future research are suggested to help image classification models be improved and relevant to real-world scenarios:

Transfer Learn in Data-Scarce Domains

Employ pre-trained models like VGG19, ResNet, Inception, and MobileNetV2 in comparatively small or imbalanced datasets to improve the performance of a limited resource model, particularly for medical imaging.

Investigate Hybrid Feature Extraction Approaches
Fusing deep learning features and handcrafted ones like SIFT, SURF, ORB will improve accuracy for applications in situations where one alone is not sufficient.

Address Class Imbalance and Dataset Bias
Utilize augmentation methods, class weighting, or even synthetic data generation (i.e., GAN) to strengthen model sensitivity regarding the underrepresented classes and their discrepancy.

Boost Interpretability and Explainability
Utilize explainable AI techniques like Grad-CAM, LIME, or any concept-based models like BotCL to ensure they can have a trusted and transparent model, especially for critical fields like healthcare.

Derive Optimized Models for Edge and Mobile Deployment
Emphasize lightweight architectures such as MobileNetV2 to enable real-time, limited-resource scenarios without sacrificing accuracy.

Adopt Advanced Data Augmentation Techniques
Tylenol with Pot may be a nasty smorgasbord of training data and augmenting strength so even for multi-label tasks.

Adhere to Standardized Benchmarks
Ensure clarity and comparability by evaluation across common datasets (e.g., ImageNet, CIFAR-10/100, Caltech-101) with the same performance measures.

Enhance Domain Adaptation Research
Facilitate WCMMDA-type mechanisms that enable cross-domain generalization so that model transfer could be made from one modality to another, say from image data to text data.

Implement Incremental and Sequential Learning
These models will develop the ability to learn newer tasks or classes over time without forgetting their existing knowledge thereby, being able to adopt flexibility in a very dynamic environment.

Promote Fair and Diverse Datasets
Promote the creation and use of diverse datasets concerning the population, lighting, and background to reduce bias and improve generalization to the real world.

Final Note
Image classification is a basic task in computer vision and has incredible potential in enabling technologies within healthcare, security, and other domains. These recommendations will allow future research to plug important holes in the current relative gaps in accuracy, fairness, efficiency, and interpretability-all leading to a close approach of AI systems to the deployment of real systems into safe, ethical, and practical applications.

VI. CONCLUSION

A thorough examination of the literature associated with image classification reveals a constantly evolving scenario buoyed mainly by innovations in deep learning, transfer learning, and hybrid approaches to feature extraction. Advances including CNNs, LSTMs with architectures like Sequencer, lightweight models like MobileNetV2, and novel training techniques such as SpliceMix and Batch Channel Normalization (BCN) have propelled further improvements in classification accuracy, generalization, and training efficiency across different datasets.

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Objectives of the Study

The principal objectives of this study were:

- To review the literature concerning image classification extensively.
- To classify, compare, and evaluate various models and techniques and their results.
- To obtain an insight into the strengths and weaknesses and practical applicability of different ways to suitable classification problems.
- Model performance is, however, seen in some results based on models that were used on datasets like ImageNet or ISIC Archive or Caltech-101 to be highly data-driven. There is no such thing as a best model; the right one should always depend on specific considerations such as complexity of the task, size of the dataset, balance between classes, and constraints on deployment.

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