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Multi-Label Image Classification: A Deep Learning-Based Systematic Review

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ABSTRACT

Multi-label image classification is an important computer vision challenge where models must predict several labels per picture since images may include many objects or features. Conventional machine learning techniques and artificial neural networks often suffered from poor classification accuracy, ineffective feature extraction, and excessive processing requirements. In order to overcome these challenges, this study examines current developments in deep learning-based MLIC and suggests an improved deep learning model that will increase classification efficiency and accuracy for big datasets. The paper examines cutting-edge designs including CNNs, RNNs, GNNs, and transformers as well as their uses in a variety of fields, such as tomato disease identification, plant disease detection, and brain tumour classification. To increase feature extraction and classification performance, the suggested model integrates noise reduction, parameter tweaking, enhanced loss functions, and attention methods. The performance of the suggested model across many training rounds is examined via extensive tests that compare its classification accuracy to that of other deep learning architectures. The results indicate that the enhanced model outperforms traditional methods, achieving higher classification accuracy and improved computational efficiency. These findings contribute to the development of scalable deep learning systems for crucial applications such as automated disease diagnosis, precision agriculture, and medical imaging.

Keywords:- Machine Learning, Multi-label image classification,Deep Learning, CNN, RNN, GNN

I. INTRODUCTION

One of the biggest problems in computer vision is image classification, which is the process of classifying pictures according to their content into specified groups. Compared to conventional machine learning techniques, this procedure is now more precise and effective because to the advancements of deep learning. Image categorisation has been transformed by deep learning models, especially CNNs (Convolutional Neural Networks), which eliminate the need for the extraction of human features. Rather, they use raw pixel data to instantly recognise traits and trends. The capacity of deep learning to interpret data via many layers gives it the ability to identify intricate structures and patterns in pictures. Numerous domains, including anomaly detection, item identification, facial recognition, and even comprehending complex real-world situations, make extensive use of these models. Deep learning, for instance, is essential for detecting disorders like tumours in medical imaging and for identifying objects and navigating highways in autonomous driving. Images and data are crucial for analysis in research and health. Researchers and medical professionals may better comprehend the anatomy and physiology of organs by using high-resolution medical photographs. Medical imaging not only helps identify illnesses but also sheds light on how various medical problems manifest and progress. In order to improve patient care, medical imaging now uses a variety of data processing methods, such as machine learning as well as deep learning. These methods aid in the effective processing of medical data, enhancing diagnosis and care in a variety of medical specialities.

II. BACKGROUND AND MOTIVATION

Sorting and labelling pictures according to their content is known as image classification in computer vision. Conventional machine learning methods like DT & SVM models as well as manually created features were used in earlier approaches. These methods were less able to handle the richness and variety of visual input as they needed human interaction to extract components like edges, textures, and forms. Although they performed well in some situations, they had trouble with big datasets and photos with complex backgrounds or a lot of variation.Deep learning has revolutionised picture categorisation by offering automatic and scalable techniques for feature extraction straight from unprocessed image data. In this area, Convolutional Neural Network (CNNs), which draw inspiration from the human visual system, have shown remarkable performance. These algorithms can successfully categorise photos across a variety of domains by first identifying low-level elements like edges & textures before learning more intricate patterns. This development has greatly increased picture classification's precision and effectiveness, making it a crucial tool for contemporary computer vision applications.

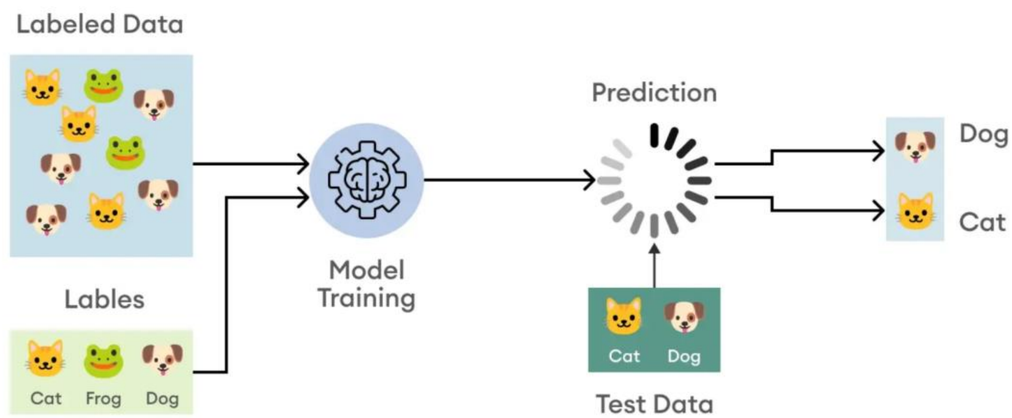

Figure 1 Workflow of Deep Learning

III. DIGITAL IMAGE PROCESSING

A subfield of computer vision systems called digital image processing helps create complex, pricy devices that mimic how human eyes work. [1] Plant disease identification, disease classification, biological processing & several scientific and technological fields are all well-known in the agricultural field [2]. The systematic process of computerising the visual representation in pixel form is known as digital image processing. This includes segmentation, filtering, and enhancement. Enhancing crucial characteristics and reducing unnecessary information about objects of interest are the primary goals of digital image processing.

IV. MACHINE LEARNING TECHNIQUES

Machine learning (ML) analyzes data, identifies patterns, and makes decisions without human intervention [3][4]. It is widely applied in wireless sensors, speech and image recognition, traffic prediction, facial detection, malware detection for cryptomining [5], cognitive radio attack detection [6], healthcare, stock trading [7], e-commerce, and fraud detection [8]. In healthcare, ML is used for disease detection, drug development, medical imaging, personalized medicine, data management, and outbreak prediction.

ML classifiers are generally divided into supervised and unsupervised types. Supervised models are trained on labeled data and validated using methods like k-fold cross-validation, while unsupervised models group unlabeled data based on shared features. Common supervised models in healthcare include SVM [9], k-nearest neighbour (KNN) [10], random forests [11], and naïve Bayes [12]. This thesis applies supervised ML classifiers for medical disease classification.

Random Forest: An ensemble of decision trees where the final output is based on majority voting among the trees, leading to strong performance [11].

SVM: Mainly used for classification, it separates classes using a hyperplane in an n-dimensional space. While linear classifiers use straight lines, SVM can apply nonlinear kernel transformations for complex problems.

KNN: Stores all training data and classifies new data by comparing it with stored samples, assigning it to the class with the closest characteristics.

Naïve Bayes: Based on Bayes' theorem, it assumes independence among features, meaning one variable does not affect another.

For medical disease classification, ML algorithms often rely on symptoms as features, which help distinguish between healthy and diseased individuals. Feature extraction techniques such as SURF [14], HOG, SIFT, LBP, and Markov feature extraction [13] are widely used, along with image processing-based methods [15].

These approaches have been applied in diagnosing numerous clinical conditions, including breast cancer [16][17], Alzheimer's disease [18], epilepsy [19], cardiovascular diseases [20], diabetic retinopathy [21], cytomegalovirus disease [22], liver transplantation [23], blood pressure estimation [24][25], Parkinson's disease [26], coeliac disease [27], leukocyte-related disorders [28], and multiple sclerosis [29].

V. DEEP LEARNING TECHNIQUES

Accurately learning intricate and unique characteristics in medical imaging with custom-made procedures and traditional ML remains a difficulty for traditional methods. Because of this, these methods often fall short when dealing with complicated medical issues. Furthermore, the accuracy of clinical data is not always dependable. It is nevertheless challenging to gather such data over extended periods of time, even when precision is excellent.The data is highly dimensional in complicated issues like text analysis and object identification, and the problem becomes increasingly non-linear. ML has developed deep learning models, which mimic the brain's structural architecture, to address this issue [31]. The organic architecture of the brain, which has several neurones connecting to one another, is used in machine learning. Neurones communicate by connecting with one another. Each neuron's contribution to the output is determined by how strongly they are connected. Figure 3 also illustrates how all neuronal inputs are added together in the cell after being weighted by strength. After conversion, the result is sent to additional neurones as a different signal.

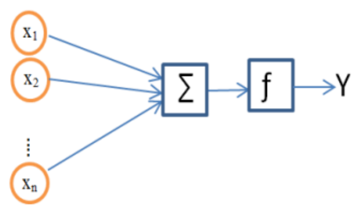

Figure 2 Basic Structure of Neuron

VI. DATASETS

High-quality datasets are essential for training deep learning models in medical and agricultural image classification. Brain tumour datasets (BRATS, Figshare) support tumour detection, plant disease datasets (PlantVillage, Cassava) enable crop illness identification, tomato-specific datasets (Tomato Leaf Disease, PlantVillage subset) focus on tomato health, and medical imaging datasets (NIH Chest X-ray 14, HAM10000) aid in diagnosing lung and skin diseases. However, challenges such as image variations, class imbalance, privacy, and data quality remain.

Table 1 Commonly Used Datasets

Aspect	Brain Tumor Dataset	Plant Disease Detection Dataset	Human Disease Detection Dataset	Tomato Disease Detection Dataset
Description	Contains MRI scans of brain tumors for classification.	Includes images of healthy and diseased plant leaves.	Medical images such as X-rays, CT scans for disease diagnosis.	Focuses on identifying various diseases in tomato plants.
Key Features	MRI images, tumor types, segmented regions.	Leaf images, disease types, healthy vs. infected labels.	X-ray, CT, and dermatology images with labeled diseases.	High-resolution tomato leaf images with disease labels.
Strengths	Essential for medical diagnosis; high-quality MRI	Useful for agricultural disease monitoring and	Helps in automated disease detection for healthcare.	Important for early detection of crop

	images.	management.		diseases.
Limitations	Limited dataset size; requires high computational power.	Variability in image quality; differences in plant conditions.	Requires expert labeling; some datasets may be imbalanced.	Complex variations in leaf images due to environmental factors.
Example Studies	BRATS, Figshare Brain Tumor Dataset studies.	PlantVillage, Cassava Leaf Disease studies.	NIH Chest X-ray, HAM10000 for skin cancer studies.	PlantVillage (Tomato Subset), Tomato Leaf Disease Dataset studies.
Feature Extraction	Texture, intensity, and shape-based features from MRI scans.	Color, texture, and morphological features of leaves.	Radiological features, lesion detection, anomaly detection.	Leaf color, edge detection, and disease-specific patterns.
Challenges	High variability in tumor shapes; difficulty in segmentation.	Different lighting conditions; similar symptoms for multiple diseases.	Data privacy issues; requirement of labeled medical images.	Environmental impact on leaf appearance; class imbalance.

VII. LITERATURE REVIEW

In many fields, but especially in medical and agricultural applications, image categorisation by machine learning and deep learning is essential. By identifying pertinent information, these techniques allow pictures to be automatically detected and classified, minimising the need for human participation. Convolutional neural network (CNNs), one kind of deep learning model, have greatly increased classification accuracy by learning hierarchical representations from massive datasets. This literature review's importance lies in giving readers a thorough grasp of the ml and dl techniques now in use for image categorisation, emphasising their advantages, disadvantages, and developments across many domains.

Md Ishtyaq Mahmud et. al [32] The goal of artificial intelligence (AI) is to create robots with human-like thought and behaviour. Deep learning, a kind of machine learning used for tasks like pattern identification, planning, and problem-solving, is one of its essential elements. Models for identifying and categorising brain tumours in medical imaging, especially when combined with magnetic resonance imaging (MRI), have been developed in large part because to deep learning approaches. Abnormal cell proliferation may result in brain tumours, which often cause neurological problems. Brain tumour survival and treatment results are greatly enhanced by early identification. A Convolutional Neural Network (CNN) model is proposed in this study to reliably detect brain tumours in MRI images. The suggested model is contrasted with popular deep learning models such as Inception V3, VGG16, and ResNet-50. Several measures, including accuracy, recall, loss, and Area Under the Curve (AUC), are used to assess these models' effectiveness. The suggested CNN model performed very well with a dataset of 3,264 MRI images, achieving 93.3% accuracy, 98.43% AUC, 91.19% recall, and 0.25 loss. The findings show that the suggested model is a trustworthy tool for the early diagnosis of various brain tumour types when compared to current models.

Harmandeep Singh Gil et. al [33] Fruit categorisation has emerged as a key field in computer vision and machine learning, and deep learning-based methods are being explored more and more for picture classification. Numerous current approaches, however, have drawbacks, including issues with feature selection, high feature volumes, and inconsistent picture quality. The quality of the features that are extracted, the kind of data that is utilised, and the classifier that is employed all have a significant impact on how well these classification systems function. A new deep learning technique that combines Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks has been presented to enhance the categorisation of fruit photos. CNN is in charge of extracting features from pictures in this method, RNN chooses the most relevant features, and LSTM uses the features that have been extracted and chosen to carry out the final classification. According to experimental findings, this hybrid approach outperforms more conventional classifiers like Support Vector

Machines (SVM), Feed-Forward Neural Networks (FFNN), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in terms of classification accuracy. This study demonstrates how well CNN, RNN, and LSTM work together to improve fruit categorisation accuracy, surpassing traditional techniques.

Table 2 Related Work on Multi Label Image Classification

Study	Focus Area	Methodology	Key Findings	Limitations
K. P. Ferentinos et al. [34]	Plant disease detection	Convolutional Neural Networks (CNN)	Achieved high classification accuracy in detecting plant diseases from leaves.	Ill-posed issues, performance depends on feature selection, variety of images, and quality of training/testing datasets.
M. Zhang and Q. Meng [35]	Citrus disease detection	Hierarchical discovery strategy for citrus canker using AdaBoost	Achieved higher classification accuracy than traditional methods for citrus canker detection.	Difficulty in detecting disease due to complex variations in leaf appearance.
S. Zhang and C. Zhang [36]	Plant disease detection	Orthogonal Locally Discriminant Projection (OLDP)	Outperformed texture analysis and neural network-based methods in disease detection.	Limited by accurate feature extraction and dimensionality reduction techniques.
A. F. Aji, Q. Munaja et al. [37]	Palm oil disease detection	Machine learning and image processing techniques (Neural networks)	Achieved 80% accuracy in detecting palm oil diseases, with potential for improvement.	Processing time optimization for mobile devices still needed, accuracy can be further improved.
B. Liu et al. [38]	Apple leaf disease detection	Deep Convolutional Neural Network (CNN)	High accuracy and quick convergence rate, with improved model robustness.	Overfitting issues and the challenge of finding the best neural network structure.
D. Pujari R [39]	Plant disease classification	Support Vector Machine (SVM) for classification of infected plant leaves	Achieved 82% accuracy in identifying pomegranate disease using image classification techniques.	Difficulty in distinguishing between infected and severely infected images.
S. P. Mohanty et al. [40]	Plant disease classification	Deep Convolutional Neural Network (CNN) architecture	Substantial reduction in accuracy (31%) due to data variation in different conditions, indicating the need for more diverse data.	Generalizability issues and reduced accuracy when images were not from the training set.
F. Martinelli et al. [41]	Disease identification challenges	Addressing computational complexity and memory constraints in disease diagnosis	Focused on reducing computational complexity, memory	High computational complexity, memory usage, and need for efficient programming.

			requirements, and the application of real-time disease diagnosis systems.	
V. K. Vishnoi [42]	Plant disease identification	Feature extraction using Gabor filter, gray level co-occurrence matrix, and NFC	Successful classification of plant leaves based on texture and shape, using neuro-fuzzy controllers and multilayered perceptron classifiers.	Difficulty in combining multiple feature types effectively with existing methods.

VIII. RESEARCH METHODOLOGY

Recent research in machine learning (ML) and deep learning (DL) follows a systematic methodology designed to ensure accuracy, reliability, and reproducibility of results. This framework typically progresses through six key stages, starting from data collection and ending with performance evaluation.

1. Data Collection and Preparation

The foundation of any ML or DL study is data. Researchers begin by sourcing datasets from publicly available repositories, online platforms, or domain-specific databases. Since raw data often contains inconsistencies, errors, or irrelevant information, it is subjected to cleaning. This includes removing duplicates, correcting errors, and ensuring uniform formatting. Normalization techniques are also applied to bring features to a similar scale, improving consistency.

Another crucial task is dataset splitting. Data is typically divided into training and testing subsets. The training set is used to teach the model, while the testing set evaluates its performance. Researchers also pay close attention to class balance so that models do not become biased toward one category. Proper partitioning reduces overfitting, ensuring that the model generalizes well to new, unseen data.

2. Data Preprocessing

Before feeding data into ML or DL models, preprocessing is necessary to make the dataset usable and effective. This stage involves multiple steps:

- Handling missing values by replacing, imputing, or removing them.
- Feature scaling and normalization to bring all features into comparable ranges.
- Encoding categorical data (like text labels) into numerical values using one-hot encoding or label encoding.
- Data transformation to highlight important features or remove noise.
- Preprocessing ensures that the model can learn efficiently, reduces computational complexity, and improves accuracy during training.

3. Model Development

Once the data is ready, researchers move to building and testing models. Different machine learning and deep learning algorithms are implemented to identify which one best suits the problem.

Frameworks such as TensorFlow, Keras, and Scikit-learn are widely used at this stage. They allow researchers to design, compile, and test different model architectures with ease. Multiple models may be experimented with to assess their adaptability, accuracy, and robustness.

4. Training and Validation

Training involves teaching the model how to recognize patterns in the training dataset. This step uses hyperparameters such as learning rate, batch size, and number of epochs. The model is trained iteratively, gradually improving its predictions.

Validation plays a vital role in avoiding overfitting—when a model performs well on training data but poorly on new data. Common strategies include cross-validation (splitting data into folds for repeated testing) and early stopping (halting training once performance stops improving). These techniques ensure that the model remains generalizable and performs reliably across diverse datasets.

5. Performance Evaluation

After training, the model's effectiveness is measured using evaluation metrics. Common metrics include:

Accuracy – overall correctness.

Precision – correctness of positive predictions.

Recall – ability to identify all relevant cases.

F1-score – balance between precision and recall.

Visualization tools such as confusion matrices, ROC curves, and precision-recall graphs are also used to gain deeper insights into performance. Comparative analysis of multiple algorithms helps identify the most efficient and reliable model for the task.

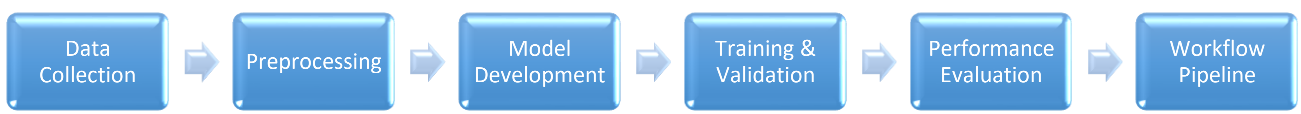

Figure 3 Flowchart for Research Methodology

IX. EVALUATION METRICS

The performance of machine learning (ML) and deep learning (DL) models in image classification is typically assessed using standard evaluation metrics. **Accuracy** remains the most widely used measure, representing the proportion of correctly classified samples over the total. However, in multi-label and imbalanced datasets, accuracy alone can be misleading, as it may fail to reflect the true performance on minority classes.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

To address this, Precision and Recall are often applied. Precision evaluates the proportion of correctly predicted positive samples among all predicted positives, while Recall measures the ability of the model to identify all actual positive instances. These two metrics are crucial in domains such as healthcare and agriculture, where false positives or false negatives can have significant consequences.

Precision and **recall** are more informative metrics in such cases. Precision, calculated as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

The F1-score, defined as the harmonic mean of precision and recall, provides a balanced perspective, especially when dealing with imbalanced datasets. Additionally, Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) curves are employed to evaluate the model's ability to distinguish between classes across different thresholds. Recall, calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Despite their importance, evaluation metrics may also highlight the limitations and failures of models. For instance, a high accuracy model may still misclassify critical disease cases if Recall is low, making it unsuitable for medical diagnosis. Similarly, in agricultural disease detection, misclassifications due to similar visual symptoms across classes can reduce both Precision and F1-score. The F1 score, calculated as:

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Therefore, a combination of metrics Accuracy, Precision, Recall, F1-score, and AUC is essential for a comprehensive evaluation. These metrics not only demonstrate how well a model works but also reveal areas where it struggles, guiding future improvements in model design and dataset balancing.

X. CHALLENGES AND LIMITATIONS

Deep learning-based image classification faces several challenges. Large, labeled datasets are required, but costly and time-consuming to collect, often leading to data imbalance and biased models. Overfitting is common with limited data, reducing generalization. Training demands high computational power, making it expensive and energy-intensive. Models act as “black boxes,” limiting interpretability in critical fields like healthcare and autonomous driving. Domain shift, adversarial attacks, and bias in training data add further risks. Large model sizes hinder real-time or low-resource deployment, while transfer learning may still suffer from overfitting or forgetting. Finally, evaluating performance requires more than accuracy, with metrics like precision and recall. Addressing these issues is vital for building efficient, ethical, and practical deep learning systems.

XI. RECENT TRENDS AND FUTURE DIRECTIONS

Recent advances in deep learning have greatly influenced multi-label image classification, particularly through transformer-based models like Vision Transformers (ViTs) and hybrid CNN-Transformer approaches that capture label dependencies using self-attention. Graph Neural Networks (GNNs) are increasingly used to model complex label relationships, while contrastive and self-supervised learning methods such as SimCLR and MoCo help improve feature representation without large labeled datasets. Meta-learning and few-shot learning provide flexibility with limited training data, and multi-modal learning that combines images with text or other data sources is growing in importance, especially in healthcare. To address label imbalance, new loss functions such as focal and asymmetric loss have been developed. Additionally, lightweight models optimized by pruning and quantization support real-time use on edge devices.

Looking ahead, research will continue to focus on explainability and interpretability to build trust in predictions. Advances in few-shot and zero-shot learning will enable recognition of unseen labels with little or no supervision. Domain adaptation and generalization, supported by synthetic data and augmentation, will help improve robustness across diverse datasets. Large-scale pretrained models like DINO and CLIP are expected to play a greater role in transfer learning for multi-label tasks. Privacy-preserving methods such as federated learning are being explored for decentralized training. Integrating classification with generative models for scene understanding and image captioning is also an emerging direction. Finally, the demand for real-time applications in healthcare, autonomous systems, and surveillance will continue driving research toward more efficient, interpretable, and practical solutions.

XII. CONCLUSION

In conclusion, deep learning developments such as transformer-based models, graph neural networks, and self-supervised learning have led to impressive advances in multi-label image categorisation. Multi-label classification is becoming more accurate and effective because to advancements in feature extraction, label dependency modelling, and generalisation. Explainability, data scarcity, and real-world adaptation are still issues, however. Enhancing interpretability, using extensive pretrained models, advancing domain generalisation, and incorporating privacy-preserving strategies like federated learning will be the key goals of future research. Multi-label classification will be essential to the advancement of AI-driven decision-making, which will guarantee more reliable and scalable solutions as real-time applications in healthcare, security, and autonomous systems continue to expand.

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