Deep Learning for Image Analysis: Trends, Challenges, and Future Directions

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ABSTRACT
Image processing is essential across various fields such as health-care, security, remote sensing, forensics, and agriculture, enabling applications like anomaly detection, pattern recognition, scene understanding, and image segmentation. With over 80% of the world's digital data now in visual form, the need for scalable, intelligent solutions is greater than ever. Deep learning (DL) and convolutional neural networks (CNNs) are outperforming untraditional methods in tasks like tumor classification, forgery detection, and object localization with their inherent ability to learn and extract deep feature-level information. Advanced architectural models. We Only Look Once (YOLO), and hybrid models have achieved significant results—CNN-based diagnostic tools now surpass 95% accuracy in detecting cancers, while YOLO variants carry out real-time detection at over 30 FPS with high precision. In the field of image forensics, deep learning models can detect splicing and copy-move forgeries with an accuracy of over 90% by extracting fine-grained artifacts invisible to the human eye. However, the field still poses significant challenges, like the limited availability of annotated datasets, and high computational needs. In high-stakes fields like healthcare, this lack of interpretability raises ethical and practical concerns. Techniques like transfer learning and data augmentation partially improve results on smaller datasets, while Explainable AI (XAI) methods—such as Grad-CAM and SHAP—are becoming essential for model transparency, interpretability, and trustworthiness. Current research is focused on enhancing model-generalizability, interpretability, and fostering interdisciplinary collaboration. As these challenges are progressively overcome, deep learning is expected to fully unlock its transformative potential across diverse image-processing domains.

General Terms
Deep Learning (DL), Image Processing, Convolutional Neural Network (CNN)

Keywords
Digital Image Processing, Image Classification, Transfer Learning, Data Augmentation, Feature Extraction

1. INTRODUCTION
Deep learning has gained significant transformative force across most of the domains of image processing. With the continuous rise of digital data, image analysis has become central to fields such as medical diagnostics, agriculture, entertainment, security, industrial automation, and autonomous navigation. Studies estimate that by the end of the year 2025, over 100 trillion images will be generated each year, emphasizing the urgent need for intelligent systems that can effectively interpret and analyze visual content.

This strategic step signals the nation's commitment to embrace advanced data science and machine learning. As big data expands in volume as well as diversity, especially in the image form, deep learning becomes an indispensable tool for deriving meaningful insights [1].

In particular, deep learning-based image compression techniques, both lossless and lossy, have shown remarkable performance by learning compact and efficient representations that preserve image quality while significantly reducing file size.[3][4] In real-world settings, deep learning models often struggle with distribution shifts, limited availability of labeled data, and adversarial attacks [5]. Without adequate training and defense strategies, such as adversarial training or preprocessing techniques, these vulnerabilities can jeopardize reliability in high-stakes applications.[6]In healthcare, interpretability is crucial. A diagnosis proposed by a model must be explainable to ensure clinical trust and accountability. This has led to increased adoption of XAI techniques such as LIME, SHAP, and Grad-CAM, which help in visualizing and justifying model predictions. A novel example of such progress is Tyche, a system designed to provide multiple plausible segmentations of medical images without requiring any retraining. By allowing users to select the most appropriate option from several label maps, Tyche helps capture image uncertainty thereby facilitating more informed clinical decision-making. Current research is focused on improving generalization, enhancing interpretability, and fostering interdisciplinary integration. As these challenges are addressed, the transformative potential of deep learning in image processing will continue to grow across diverse sectors, from precision agriculture.

This survey paper is based on recent literature on deep learning in image processing. Rather than emphasizing architectural innovations or benchmarks.

2. LITERATURE REVIEW
Each paper reviewed in this survey is evaluated based on the following key aspects:

- **Advantages**: What are the main contributions of the paper? What innovations or performance improvements do it bring to the field?
- **Limitations**: What key challenges or obstacles are identified by the authors? Are there issues related to scalability, robustness, data dependency, or interpretability?
- **Future Scope**: What do the authors suggest as possible future improvements or extensions of their work? Are there any unresolved questions or hypotheses?

Also, by identifying common patterns in techniques and challenges addressed, an analysis table is presented at the end.

2.1 Deep Learning for Medical Image Processing: Overview, Challenges and Future [7]

Deep learning has revolutionized medical image processing, significantly improving disease diagnosis, treatment planning, and almost all healthcare automation. It highlights the limitations of traditional computer-aided diagnosis (CAD) systems, which rely on handcrafted features and domain knowledge. In contrast DL, particularly CNNs, offers superior performance by learning hierarchical features directly from raw medical images, enabling higher diagnostic accuracy, efficient feature extraction, and robust model generalization. Core medical imaging tasks such as segmentation, classification, detection, and registration are thoroughly examined. These are essential for identifying anatomical structures, detecting abnormalities, categorizing disease states, and aligning images. Real-world applications are extensively reviewed across imaging modalities and diseases. In gastrointestinal imaging, deep networks assist in polyp localization and bleeding detection using capsule endoscopy, while cardiac imaging benefits from automated calcium scoring and hybrid CNN-SVM approaches for tumor detection.

Advantages: Deep learning offers numerous advantages in medical image processing complex features for manual feature engineering. It enhances diagnostic accuracy, speeds up analysis, and supports large-scale data handling. Deep learning models have exceptional performance across various medical imaging modalities, often surpassing traditional machine learning techniques. Their adaptability also allows for real-time application and integration with other healthcare technologies.

Limitations: Despite its potential, deep learning faces several limitations in the medical domain. One major issue is the scarcity of annotated data, as labeling requires domain expertise and is time-consuming. Class imbalance, especially for rare diseases, can hinder model performance. Additionally, variations in imaging protocols and patient anatomy reduce model generalizability.

Future Scope: The future of deep learning in medical imaging lies in developing more explainable models, integrating multi-data (such as combining imaging with electronic health records and enhancing real-time processing through edge computing. Collaborative efforts among clinicians and AI researchers.

2.2 Deeplearning-based speckle imagesuper-resolution for digital image correlation measurement [8]

Specialized deep learning method to enhance low-resolution (LR) speckle images. Since DIC relies on high-resolution (HR) images of randomly patterned speckles for accurate results, traditional methods require expensive imaging equipment and large storage, making the process costly and inefficient. The authors introduce a custom neural network called SISRN (Speckle Im- age Super-Resolution Network) designed specifically to recover fine speckle details and maintain the statistical properties unique to DIC images. The model is trained using synthetic LR-HR image pairs with an L1 loss function and optimized using Adam, targeting a 4× resolution improvement. Experimental results show that SISRN outperforms traditional interpolation methods and even general-purpose super-resolution models in terms of PSNR, SSIM, and DIC measurement accuracy. It is validated through rigid body translation and uniaxial tensile tests, demonstrating that the strain and displacement measurements using SISRN-enhanced images closely match those obtained using original HR images.

Advantages: The SISRN model allows high-accuracy D'IC using low-resolution images, making it cost-effective by reducing the need for expensive high-resolution cameras. It is uniquely designed to preserve the random texture of speckle patterns, which is essential for accurate strain and displacement measurement. Its architecture, built on residual blocks and sub-pixel convolutions, ensures high performance with manageable computational complexity. The model also helps reduce image storage needs and was successfully validated on real test cases, like rigid translation and tensile testing.

Limitations: One major limitation is that the model was trained on synthetically down sampled images, which may not capture real-world noise or distortions. Being highly task-specific, the model is not suitable for general-purpose image enhancement without significant changes.

Future Scope: Future work can involve training the model on real-world LR-HR speckle image pairs to improve its robustness and generalization. There's also potential to develop a multi-scale version of SISRN that handles different upscaling factors. Integrating the model into DIC analysis software could enable real-time super-resolution before measurements. Improving its performance under noise, blur, or lighting variations is another valuable direction. Finally, SISRN's approach could be adapted to other fields like medical imaging or microscopy where random textures play a key role.

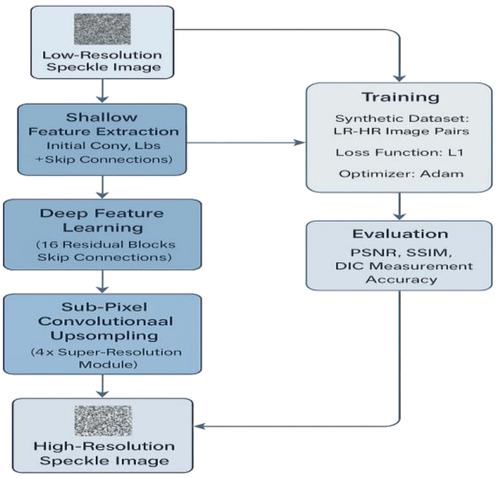

Fig. 1: SISRN Framework

2.3 Deep Learning-Based Digital Image Forgery Detection System [9]

This study presents a robust deep learning-based system for detecting digital image forgery, specifically focusing on image splicing, a common tampering method where parts from one image are inserted into another to fabricate a misleading yet realistic visual. These manipulations often leave no obvious perceptual clues. To counter increasingly sophisticated forgeries, the proposed hybrid model integrates ResNet50v2, known for its deep residual learning, with pre-trained YOLO CNN weights via transfer learning. This fusion enables efficient training and powerful feature extraction, effectively distinguishing between authentic and tampered regions of images.

Advantages: The primary strength of this approach lies in effectively combining ResNet50v2 and pre-trained YOLO CNN weights through transfer learning, resulting in high accuracy, reduced training time and thus less computational power. It excels at detecting image splicing by learning complex visual features.

Limitations: Despite strong performance in controlled conditions, the system shows reduced accuracy under challenging scenarios such as poor lighting, motion blur, or surface reflection. The segmentation model struggles to generalize across drastically different image qualities and tool geometries.

Future Scope: Future efforts can improve by incorporating real-time image capture with edge processing and exploring self- or semi-supervised learning could reduce reliance on manual labeling. It has the potential to be integrated into smart manufacturing and Industrial IoT environments, providing real-time monitoring and decision support to reduce downtime and improve operational efficiency.

2.4 Deep Learning in Big Data, Image, and Signal Processing in the Modern Digital Age [13]

Comprehensive editorial overview of 25 cutting-edge contributions in a Special Issue, highlighting how deep learning is revolutionizing rapid growth of internet-connected systems producing large volumes of heterogeneous data, traditional processing techniques struggle with scalability and efficiency. Deep learning, with its powerful pattern recognition and feature extraction, offers a robust solution for interpreting raw, un- structured and unlabeled data. Its applications span medical informatics, weather prediction, cybersecurity, industrial IoT, finance, and education. In healthcare, deep learning aids in analyzing medical images, signals from wellness devices, and large-scale datasets from hospital information systems, for example, detecting COVID-19 from chest X-rays, interpreting EEG signals for eye state recognition, and classifying mental health conditions like depression. In remote sensing, GAN-based models such as ESRGAN and Kernel GAN enhance satellite image resolution for disaster monitoring and urban development. Deep CNNs are also applied to classify sky/cloud patterns crucial for weather forecasting. In cybersecurity, deep learning enables malware detection, VPN traffic analysis, and anomaly detection to provide scalable, distributed security systems. In finance and business, sentiment-aware RNNs forecast stock trends from Twitter data, while ensemble neural networks predict academic outcomes using behavioral and demographic data.

Advantages: This paper underscores the deep learning's versatility in processing vast and complex datasets across diverse domains making it a cornerstone technology in the modern digital era. Its ability to learn from unlabeled and diverse data types allows for automation and intelligent decision-making in fields ranging from healthcare and industry to security.

Limitations: Despite its promise, deep learning faces several limitations. Issues like model generalizability, data privacy, and reliability issues.

Future Scope: To tackle these challenges, the paper recommends creating lightweight, energy-efficient models and placing a stronger emphasis on explainable AI. It also highlights the adoption of self- supervised learning, enhanced data augmentation, federated learning for privacy-preserving decentralized training, and improved cross-domain generalization.

2.5 Digital image forgery detection using deep learning approach [14]

Deep learning-driven approach to identify image forgeries, focusing specifically on the common splicing technique, where elements from one image are seamlessly inserted into another to produce a realistic yet altered composite. Traditional approaches to forgery detection often fall short when faced with sophisticated manipulations or post-processing techniques like compression. To address these challenges, the authors proposed a patch-based classification method utilizing a CNN architecture based on VGG-16. The model is trained to classify small image patches (40×40 pixels) as either genuine or tampered. This patch-based approach enables the network to capture subtle differences between authentic and forged regions while simplifying the training process, allowing effective performance even with limited data. The model records a classification accuracy of 97.8% when fine-tuned with pre-trained weights and 96.4% when trained from scratch (zero-stage model). These results surpass the performance of many existing forgery detection methods, like DCT analysis, Markov models, and chroma-based feature extraction. Overall, the study highlights the potential of deep CNNs with transfer learning to provide effective and scalable solutions for verifying digital image integrity.

Advantages: The proposed approach demonstrates excellent accuracy in detecting image splicing, outperforming traditional methods and showing strong resilience against image distortions and compression. Its use of the well-established CNN based VGG-16 model allows for effective feature extraction and classification by employing a patch-based classification strategy.

Limitations: While the model performs well on uncompressed data, its accuracy significantly decreases under JPEG compression (down to 66%), i.e., when exposed to post-processing operations, indicating a need for improved robustness in real-world conditions. Additionally, the approach is restricted to classification and does not localize the manipulated regions within an image.

Future Scope: Future work should expand the model to detect diverse forgery types, such as copy-move, retouching, and deepfakes, while improving robustness against post-processing effects like compression, resizing, and noise. The author also suggests evaluating the system using alternative architectures like Mobile Net or ResNet-50 for improved efficiency and incorporating localization techniques to not only detect but also highlight tampered regions. Additionally, training on more varied datasets could enhance the model's generalizability across different manipulation styles and image sources.

2.6 Bidirectional graphics-based digital twin framework for quantifying seismic damage of structures using deep learning networks [15]

This paper introduces a goal is to simulate realistic earthquake damage (forward prediction) and predict structural conditions such as drift, stress, and strain (backward prediction) using images captured during post-earthquake inspections. The framework starts by developing a Graphics-Based Digital Twin (GBDT) that integrates finite element (FE) modeling using a software called Abaqus using a method known as Concrete Damage Plasticity Model (CDPM) to realistically simulate cracks and damage. They then turn this damage into images by projecting it onto a 3D model using Blender. These images are made to look realistic by adding textures and noise using tools like Perlin noise, displacement maps, and normal maps. These images serve as training data for deep learning networks. For backward prediction, the framework uses Residual Neural Networks (ResNet) in the Dam- age 2Drift (D2Drift) model to estimate maximum drift. The framework closes the loop by demonstrating that real or rendered photographic images can be used to detect damage and estimate structural conditions, effectively bridging the gap between visible damage and structural integrity assessment. Overall, Bi-GBDT represents a significant step toward enabling fast, reliable, and automated post-earthquake structural assessments using drone imagery and deep learning.

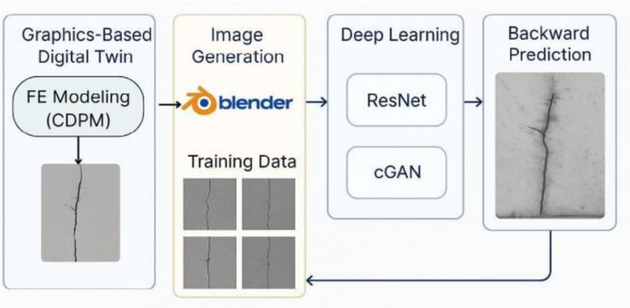

Fig. 2: Bi-GBDT Framework

Advantages: The Bi-GBDT framework is designed to quickly and automatically assess damage after an earthquake by utilizing synthetic data and deep learning techniques. It effectively creates realistic simulations of structural damage through a Graphics-Based Digital Twin (GBDT) and trains accurate models like ResNet and cGANs to predict structural conditions from images. The approach reduces the need for manual inspections and performs well even on real experimental data, making it ideal for rapid and safe damage evaluation using drone imagery.

Limitations: The system heavily relies on synthetic data, which may not fully capture the complexity of real-world damage. It has been tested mainly on a concrete shear wall, so its generalizability to other structures is still limited. Also, factors like lighting, image noise, or irregular damage patterns in real environments could affect its performance.

Future Scope: Future work can focus on expanding the framework to different structures and using real earthquake images to improve model accuracy. Enhancing the realism of simulated damage and integrating the system with drone platforms can make it a practical tool for real-time structural health monitoring in disaster response.

2.7 Learning deep neural networks' architectures using differential evolution. Case study: Medical imaging processing [16]

The paper proposes a novel method for automatically designing CNN architecture using Differential Evolution (DE), a nature-inspired optimization algorithm. Instead of manually selecting the number of layers, filters, and other hyperparameters, the DE algorithm evolves CNN structures over multiple generations by simulating processes like mutation, recombination, and selection. The study concludes that DE is an effective and efficient strategy for automating CNN design, particularly in the context of digital medical image analysis.

Advantages: The proposed method eliminates the need for a manual design of CNN architectures, saving time and reducing human bias in the model configuration. The approach is also versatile, working well across different types of medical images like MRI scans, histopathology slides, and ultrasounds. Moreover, it demonstrates strong classification performance, often matching or surpassing well-established deep learning models, with robust statistical validation.

Limitations: One limitation of the study is that the evolved CNN architectures using the networks were trained from scratch without leveraging pre-trained models, which could lead to longer training times and possibly lower performance in low-data scenarios. The computational cost of training multiple CNNs over several generations, though manageable, may still be high for some users without access to GPUs.

Future Scope: Future work could focus on expanding the architecture encoding scheme to allow varying numbers of hidden units across layers, increasing the model's adaptability. Incorporating pretrained CNNs into the evolution process could further enhance performance and reduce training time. The approach can also be extended to include other types of neural layers image analysis.

2.8 Deep Learning-Based Land Cover Extraction from Very-High-Resolution Satellite Imagery for Assisting Large-Scale Topographic Map Production [17]

The research paper addresses Indonesia's urgent need for large-scale topographic mapping to support infrastructure, planning, and public services. The system's automation makes it highly applicable for real-time urban planning environmental monitoring, disaster response, and resource management. Its modular design also allows easy integration of more land cover classes and spatial data, enhancing its utility for scalable, accurate topographic map production.

Advantages: The deep learning-based approach significantly speeds up land cover extraction speed and accuracy from high-resolution satellite imagery, reducing processing time from days to under an hour per map sheet. It operates continuously with minimal human input and achieves high accuracy. Using U-Net architecture with a ResNet34 encoder and PCA-based feature selection enhances model performance, making the method efficient, scalable, and ideal for applications like urban planning and disaster response.

Limitations: Despite its success, the study also notes limitations, particularly due to the limited diversity and geographic scope of the training dataset. It is restricted in classifying only four land cover types; hence, the model's generalizability to other regions or more diverse classes remains constrained. Its performance can vary across different regions and requires post-processing to remove noise.

Future Scope: For future work, the authors propose exploring more advanced architecture. A comparative analysis of such architectures could also lead to more optimized frameworks tailored for scalable and accurate topographic map production.

2.9 Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture [18]

This is based on the role of DL and computer vision enable rapid, accurate, non-destructive and automated disease diagnostic tools, revolutionizing monitoring and management practices in agriculture. The review analyzes over 278 research articles and highlights key imaging techniques like RGB, multispectral, hyperspectral, thermal, fluorescence, microscopic, and X-ray imaging, all crucial for early disease detection. It evaluates DL architecture. A major focus is on multimodal DL, which fuses spectral, visual, and textual data to build more robust detection systems. It also emphasizes practical deployment challenges, recommending standardized datasets, better annotation quality, and lightweight models suited for edge computing in real agricultural environments. Further, it explores emerging technologies such as AI-integrated IoT systems for real-time field monitoring, smart segmentation for handling large datasets, cloud computing for scalable remote diagnostics, and XAI to improve transparency for end-users like farmers and agronomists.Overall, the integration of DL in precision agriculture enables early intervention, automated monitoring, and more informed decision-making, thereby boosting productivity, strengthening crop protection, and accelerating disease detection, and ultimately contributing significantly to global food security.

Advantages: Deep learning enables fast, non-destructive, and highly accurate plant disease detection, automating feature extraction and improving diagnostic consistency. Advanced imaging technologies. Multimodal learning enhances robustness and adaptability across diverse agricultural environments, supporting real-time, scalable monitoring.

Limitations: Despite its benefits, several limitations remain. Deep learning models often face reduced performance in real-world settings due to environmental factors like lighting variations, background clutter, and image noise.

Future Scope: The author proposes that future scope should focus on developing lightweight, interpretable, field-ready DL models for diverse agricultural environments, integrating XAI for transparency, and using edge/cloud computing for real-time and large-scale deployment. Emphasis should also be placed on multimodal and transfer learning approaches that fuse different data types and adapt models to new conditions with limited data. To support these efforts, larger, annotated, and diverse datasets must be created for accuracy in plant disease detection.

2.10 Deep learning based denoising and enhancement of satellite images using DA-CNN and ORHE techniques [19]

The study proposes a hybrid DL-based on technical factors during transmission, affecting remote sensing analysis. Traditional denoising techniques blur edges, reducing image quality. The paper introduces a three-part solution:

(1) DA-CNN (Denoised Attention-Convolutional Neural Network)
(2) ORHE (Optimized Reformed Histogram Equalization)
(3) ISSO (Improved Shark Smell Optimization)

The framework was tested on a Kaggle satellite dataset and real-time ISRO data, achieving strong results in both visual and numerical metrics. By combining DA-CNN for effective noise removal, ORHE for automated contrast improvement, and ISSO for fine-tuning, the framework delivers superior image clarity and edge preservation. It is highly applicable in remote sensing, disaster monitoring, and land use analysis, offering fast and accurate preprocessing for satellite imagery.

Advantages: The proposed approach offers high-performance denoising and enhancement by combining the strengths of deep learning and adaptive histogram techniques. DA-CNN preserves important features like edges and textures while effectively removing noise, and ORHE automatically adjusts contrast without manual input, enhancing visual quality. The model achieves excellent accuracy metrics and is applicable to real-world satellite data, making it a valuable tool for remote sensing tasks.

Limitations: While the proposed framework shows great potential in denoising and enhancement, the proposed framework faces several practical issues. Its generalizability is yet to be fully established due to insufficient testing on extremely low-resolution or highly distorted images. Also, challenges concerning interpretability and parameter tuning may also hinder its accessibility for non-expert users, creating obstacles for its broad, easy-to-use deployment.

Future Scope: Future work should focus on developing lightweight, resource-efficient architectures, exploring data-efficient learning methods, and improving generalization across varying image qualities and terrains. Enhancing explainability, enabling adaptive parameter tuning, and integrating the model into broader Earth observation pipelines will further strengthen its real-world applicability.

2.11 Recent Advances in Deep Learning-Based Spatiotemporal Fusion Methods for Remote Sensing Images [20]

Deep learning-based spatiotemporal fusion (DL-STF) methods have emerged as powerful alternatives, capable of automatically learning nonlinear relationships, extracting intricate features, andoffering improved adaptability across diverse scenarios. The study classifies existing DL-STF approaches into four primary categories:

(1) **CNN-based methods** – effective for spatial feature extraction and have enhanced through residual and attention modules
(2) **GAN-based method**s – capable of generating high-quality, realistic images using adversarial learning, ideal for sparse or noisy data
(3) **Transformer-based methods** – powerful in handling long-range spatial and temporal dependencies using self-attention mechanisms for capturing global contextual information
(4) **Diffusion-based methods** – emerging techniques that leverages probabilistic noise modeling and denoising processes to produce highly accurate and stable fused imagery.

Advantages: Deep learning has greatly enhanced spatiotemporal fusion by enabling the seamless integration of diverse satellite imagery with improved high accuracy, automated feature extraction, and greater adaptability. Models such as CNNs, GANs, and Transformers efficiently capture complex spatial and temporal dependencies, outperforming traditional fusion methods. These techniques allow more precise land monitoring, resource management, and environmental assessment, while also expanding the potential of remote sensing data dynamic real-world challenges.

Limitations: Despite their success, DL-STF methods face several limitations. They require high computational power, large and high-quality datasets, and often struggle with sensor inconsistencies and dynamic changes in land cover. The lack of standardized evaluation protocols further complicates benchmarking and comparison across different approaches.

Future Scope: Future research should focus on developing lightweight, real-time models, enhancing adaptability using multi-scale and attention mechanisms, and handling sensor mismatches with learned alignments. Integrating physical models, enhancing explainability, and creating benchmark datasets will further strengthen the reliability and scalability of DL-STF systems for wider operational use.

2.12 An Exhaustive Review on Deep Learning for Advanced Landslide Detection and Prediction from Multi-Source Satellite Imagery [21]

This paper presents a comprehensive review and proposed framework for improving landslide detection and prediction using DL techniques with multi-source satellite data. Landslides pose severe risks to life, infrastructure, and ecosystems, making accurate, timely detection important. Traditional approaches (e.g., manual surveys basic image analysis) lack scalability and precision in complex terrains. To address this gap, the study integrates DL within the remote sensing workflow. The proposed framework leverages Sentinel-2 multispectral imagery, slope data from ALOS PALSAR, and elevation data from Digital Elevation Models (DEM). These data sources are crucial in capturing environmental variables like vegetation density, rainfall patterns, and terrain structure, all of which are directly linked to landslide susceptibility. The integration of spectral, slope, and elevation data with DL significantly reduces misclassification errors common in traditional methods due to limited feature depth. Ultimately, the paper shows how integrating DL with satellite data transforms landslide detection from a post-event analysis tool into a scalable, real-time, and proactive decision-making framework.

Advantages: The integration of deep learning with multi-source satellite data significantly improves the accuracy and scalability of landslide detection. By using rich spectral, slope, and elevation features along with powerful segmentation models, the system can handle complex terrains and diverse environmental conditions. The approach supports early warning systems and can be effectively used in disaster mitigation, risk assessment, and land management planning, offering a robust, data-driven solution to an otherwise unpredictable natural hazard.

Limitations: Despite its advancements, the system requires high-quality satellite imagery, consistent data availability, and significant computational resources for training deep learning models.

Future Scope: For future work, it suggests real-time monitoring via edge computing, integrating geophysical knowledge for better interpretability, creating benchmark datasets, and promoting collaboration to build deployable, scalable solutions.

2.13Current trends on the use of deep learning methods for image analysis in energy applications [22]

This paper is based on a thorough review of the growing role of DL—especially CNNs and encoder–decoder networks—is applied to monitor and forecast renewable energy sources like solar and wind. These models process sky, satellite, and rooftop images to predict irradiance, detect defects in solar panels and wind turbines, and assess solar energy potential. FCN are particularly effective in segmentation tasks such as identifying suitable rooftops for solar installations or mapping existing photovoltaic systems at a large scale. The devices category involves operational monitoring and diagnostics. CNNs and Mask R-CNNs are widely used to analyze thermal and infrared images for fault detection in electrical components, motors, and power systems. DL is also used to monitor battery health, estimate the state of charge, predict remaining useful life, and analyze heat distribution in buildings for improved energy efficiency. Overall, the paper emphasizes DL's growing potential to revolutionize energy monitoring, forecasting, and material innovation through continued interdisciplinary collaboration.

Advantages: Deep learning, particularly CNNs, offers powerful tools for handling complex image data in energy applications. It enables accurate classification, object detection, and segmentation across various scales—from identifying faults in solar panels and wind turbines to analyzing microstructures of battery materials. DL models can process large datasets efficiently, uncover patterns not easily detected by traditional methods, and automate monitoring tasks, thereby improving system reliability, predictive maintenance, and decision-making in energy management.

Limitations: Despite its potential, deep learning faces several challenges in energy applications. Many energy datasets are noisy, irregular, or limited in size, making model training difficult. DL models often require significant computational resources and lack transparency, which can hinder interpretability and trust especially in safety-critical systems. Moreover, they are not inherently de- signed to handle temporal or spatial dynamics and adapting them to energy-sector requirements often demands domain-specific tuning, data preprocessing, and integration with physical laws.

Future Scope: The future of DL in energy lies in developing more interpretable, resource-efficient models tailored to real-world constraints. Techniques like Physics-Informed Neural Networks (PINNs) offer promising ways to embed domain knowledge into DL frameworks.

2.14Detection of sick broilers by digital image processing and deep learning [23]

This paper presents a robust, intelligent system for automated detection of sick broilers by integrating DIP with advanced

DL models. It addresses the limitations of traditional poultry health monitoring, which is often manual, subjective, time-consuming and error prone. Aiming for early, scalable disease detection in commercial farms, the system uses visual data to assess broiler health in a non-invasive and efficient manner. Video footage from real poultry environments was collected, capturing various behaviors and lighting conditions. Two deep learning approaches were used. Both models proved highly adaptable to dynamic farm conditions and demonstrated the effectiveness of deep learning in real-time poultry health monitoring, reducing manual labor, enabling early detection of illness, and enhancing overall animal welfare and farm productivity. Figure 3 shows the proposed methodology.

Advantages: The system offers over 95% accuracy in detecting sick broilers through real-time, non-invasive image analysis. By evaluating behavioral cues like posture and movement, it reduces manual labor, enhances early detection, and improves animal welfare and farm efficiency.

Limitations: Despite its effectiveness, the system has some limitations. It depends solely on visible behavioral signs, making it less effective for detecting illnesses without clear external symptoms.

Future Scope: Future developments recommended by the author might incorporate more data sources, such as thermal imaging, aural cues, and multi-angle camera setups to record a wider variety of health indicators, to increase their efficacy.

3. ANALYSIS TABLE

The analysis of the techniques and methods used by various research papers on DL algorithms for image analysis.

Table 1:Overview of DL Techniques Surveyed in Image Analysis

Sr. No	Paper Title	Techniques	Addressed Issue
1	Deep Learning for Medical Image Processing: Overview, Challenges and Future [7]	CNNs, RNNs, AlexNet, VG- GNet, GoogLeNet, ResNet, U- Net	Limitations of traditional CAD systems, lack of automation, data scarcity in healthcare imaging
2	Deep learning-based speckle image super-resolution for digital image correlation measurement [8]	SISRN (novelframework) based on DL	DIC using low-resolution speckle images
3	Deep Learning-Based Digital Image Forgery Detection System [9]	ResNet50v2, YOLO CNN	Detecting manipulated/forged images, image tampering (splicing)
4	Deep Learning in Big Data, Image and Signal Processing in the Modern Digital Age [13]	Deep CNNs, GANs, Transfer Learning	Efficient processing of large unstructured data, scalability issues, limitations of traditional methods
5	Digital image forgery detection using deep learning approach [14]	VGG-16 CNN	Detecting image splicing
6	Bidirectional graphics-based digital twin framework for quantifying seismic damage of structures using deep learning networks [15]	Bi-GBDT (novel framework) integrating ResNet and cGANs	Post-earthquake structural damage assessment
7	Learning deep neural networks' architectures using differential evolution. Case study: Medical imaging processing [16]	Differential Evolution	Automated method for designing CNN for medical image analysis
8	Deep Learning-Based Land Cover Extraction from Very- High-ResolutionSatellite Imagery for Assisting Large-Scale Topographic Map Production [17]	U-Net,ResNet34, Semantic, Segmentation, Pan-sharpened Imagery	Topographic map production, slow land cover classification, manual mapping inefficiency, need for real-time spatial data
9	Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture [18]	DL models (CNNs, ViTs, GANs), Computer Vision, Imaging Techniques (RGB, multispectral, hyperspectral etc.)	Manual and error-prone plant disease detection
10	Deep learning based denoising and enhancement of satellite images using DA-CNN and ORHE techniques [19]	DA-CNN, ORHE, ISSO algorithm	Satellite image distortion/noise, edge blurring, enhancement
11	Recent Advances in Deep Learning-Based Spatiotemporal Fusion Methods for Remote Sensing Images [20]	CNNs, GANs,Transformers, Diffusion Models	Spatial/temporal resolution trade-off, fusion technique limits
12	An Exhaustive Review on Deep Learning for Advanced Landslide Detection and Prediction from Multi-Source Satellite Imagery [21]	DeepLabV3+,HRNet,ResUNet, SegFormer, and U-Net	Landslide detection for risk mitigation

13	Current trends in the use of deep learning methods for image analysis in energy applications [22]	CNNs, FCNs, Mask R-CNN,GANs, encoder–decoder architectures	Image-based challenges in energy sector
14	Detection of sick broilers by digital image processing and deep learning [23]	YOLOv3, IFSSD with InceptionV3,feature pyramid networks	Limitations of manual broiler health monitoring

4. CONCLUSION

Deep learning has emerged as a dominant approach in image analysis, consistently outperforming traditional methods in healthcare, agriculture, remote sensing, manufacturing, and digital forensics. Across most of the surveyed literature, CNNs remain the foundational architecture, often enhanced by frameworks like U-Net, ResNet, YOLO, DeepLab, and GANs like classification, segmentation, detection, and image enhancement. These techniques tackle issues such as visual noise, spatial-temporal resolution gaps, manual annotation inefficiencies, and domain inconsistency. To address challenges like data scarcity, class imbalance, and overfitting, techniques such as transfer learning, data augmentation, and hybrid models (e.g., CNN-RNN, ELM- RVFL) are commonly applied. While traditional techniques such as filtering, morphological operations, and feature extraction are interpretable, lightweight, and computationally efficient, they often fall short in handling complex tasks that require contextual understanding, multi-modal data analysis, or high pattern variability. However, when combined with deep learning approaches, they can significantly enhance interpretability and overall accuracy. Despite these advances, common limitations that persist across domain include high computational requirements, dependence on extensive labeled datasets, limited generalizability, and interpretability challenges. However, new approaches that use lightweight models, transformer-based architectures, and XAI frameworks suggest promising avenues for future exploration. Ultimately, the fusion of deep learning with domain-specific knowledge and traditional methods is driving the development of intelligent, scalable, and real-time image processing solutions within various industries.

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