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Cross-Domain Deep Learning Techniques for Enhanced Diagnostic and Phenotyping in Medical and Agricultural Imaging: Bridging Computer Science and Healthcare Management

Dr K.Madan Mohan[1],Mohammad Chand Jamali[2],Mohammed Abdalhamied M. Abushohada[3],Syeda arbeena kausar[4],Seema Firdose[5],Dr. R. Sivaraman[6]

[1]Associate Professor, Department of CSE (AI&ML), Malla Reddy College of Engineering
Secunderabad, Telangana, 500014, India
[2]Assistant Professor, Faculty of Medical and Health Sciences, Liwa College, Al Ain, Abu Dhabi, United Arab Emirates
[3]Assistant Professor, Faculty of Medical and Health Sciences, Liwa College, Abu Dhabi, United Arab Emira
[4]Assistant Professor
Computer Science and Engineering Department, VVIET, Mysore, Karnataka, India
[5]Assistant Professor
CSE Department, Vidya Vikas Institute of Engineering and Technology
Mysore, Karnataka
[6]Associate Professor
Mathematics Department
Dwaraka Doss Goverdhan Doss Vaishnav College, Arumbakkam, Chennai – 600106, India

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Abstract: In this study, deep learning has been investigated in clinical analysis, in terms of increasing the precision and speed in diseases identification, image division and features identification in various systems of bioscience. The CNN, U-net, and GAN deep learning algorithms used have been developed to accomplish a range of image and classification processes. The CNN-based model in healthcare was 92% diagnostically accurate, and the U-Net model was 89% accurate in segmenting medical images. In agriculture, CNN model when applied to plant disease detection had an accuracy of 87%; GANs were utilized for generation of synthetic data thus enhancing the performance of model training. Stakeholders' findings demonstrate that the application of AI can considerably decrease diagnostic time and improve accuracy in most cases in both fields. Synthetic data generation also played a big role in avoiding issues caused by the small, labeled datasets, especially in terms of generalization of models. It highlights revolutionizing the diagnostic process using cross-domain deep learning applications and provides information for a new era of healthcare management and agriculture.

Keywords: *Deep learning, diagnostic accuracy, image segmentation, synthetic data, healthcare and agriculture.*

I. INTRODUCTION

The incorporation of deep learning approaches has proven to be relevant as well as feasible in many fields such as medical diagnosis and agriculture phenotyping among others. On the surface, these two domains seem to be diverse, however, they share similar issues at the keyword level during the aggregation of massive amounts of intricate images. Medical imaging because of focusing on diagnosis and therapy is revolutionized with deep learning to study the important features of X-rays, MRI, and CT scans. Agriculteral imaging is also essential for plant phenotyping: learning plant characteristics, disease and the growth process; all these are essential if the best exposure in agricultural practices for maximum production is to be employed [1]. This paper explores the application of deep learning that extends from health to other disciplines, specifically revisiting medical diagnosis but also expanding into agricultural phenotyping. This study will draw other methodologies from computer science since it is analysing how models developed in one field can be useful to the other with an intention of enhancing both fields [2]. For example, a deep learning model developed to analyze medical images can be used to detect diseases in crops or check growth environments and vice versa. It may be expected that such cross-area application will make image processing and data analysis in the two fields more efficient and accurate, hence enhancing the diagnostic capability of health and the phenotyping capability of agriculture respectively [3]. Besides, such opportunities may open a new interdisciplinary field for healthcare management and agricultural development cooperation. Such interdisciplinary innovation in this regard would mean cooperating those in computer science, health, and farming who track down some of the toughest problems in each discipline. This research aims at filling the gap between these two fields and brings a new perspective in the deployment of deep learning as well as AI technologies in various domains.

II. RELATED WORKS

The automation of agriculture, healthcare and veterinary health through deep learning and AI seems to have potential in the optimization of diagnostic procedures. For example, in the agricultural sector, Elsherbiny et al (2024) proposed deep learning-based model to quickly detect robust health of grapes using digital images. The study, therefore, poses a spotlight on the use of AI to fasten disease detection and the subsequent decreased reliance on traditional, manual diagnostics for enhanced precision agriculture and accuracy [16]. Similarly, Grishina et al. (2024) applied chlorophyll fluorescence imaging to identify infections of plants. This technique, which is specific to agricultural applications, gives sense of what advanced imaging with AI could do for monitoring plant health. This research provides new avenues for the parallel use of similar deep learning techniques in medical diagnostics, in which image analysis can improve the detection and classification of diseases [21]. In the field of synthetic data generation, Goyal and Mahmoud (2024) reviewed techniques that used generative AI, a component which is critical to AI model development. It becomes easier to overcome the data scarcity problem, particularly in healthcare and agriculture, for which it is challenging to find labeled data. With the aid of synthetic data, the systems are robust and ready to tackle real-world diversity; thus, this has proven useful in training diagnostic models for both plant disease identification and medical condition detection [20]. AI has also revolutionized medical imaging. Lei et al. (2024) demonstrated deep learning implementation in agricultural image segmentation where it plays a critical role in raising the diagnostic accuracy. In medical imaging, segmentation would be quite simple, and easy to be applied for which the various structures of organs can be segmented for enhanced identification and treatment of tumours or abnormalities [24]. In veterinary medicine, Farschtschi et al. (2024) studied the use of digital holographic microscopy for the observation of leukocytes in dairy cow blood and milk. This technique, which images without labeling, opens new ways for veterinary diagnostics, by which infections or diseases may be tracked and monitored in animals better. Such techniques can find their mirror images in the human health care system too, especially in diagnostic imaging and disease monitoring [17]. Additionally, Kamariankis et al. (2024) created a low-cost linear robotic camera system intended to monitor the growth of plants in greenhouses. This technology exemplifies how deep learning systems can be used in practical applications of agriculture, ensuring precise and automated monitoring can be implemented even with limited budgets. The idea of cost-effective AI-based diagnostic systems directly translates to healthcare, where cheap diagnostic equipment is required to enhance the availability of medical services [22]. Another veterinary use was reported by Li et al. (2022) which involved sophisticated methods of diagnosing fish diseases using AI also utilizing machine learning and image analysis in monitoring and maintaining animal health. This continues to expand the scope of usage of AI not only for agriculture and healthcare but also for even larger biological systems where diagnostics should be fast and effective for healthy living organisms to be assured [25].

Also, Korkmaz et al. (2024) described research concerning the detection of threats posed by various dangers to farm animals via deep learning models. A comparative study on various AI models that could detect diseases in addition to other hazards towards the health of animals is included in the study. These deep learning models also improve the detection rate considerably and are highly required in animal care as it involves animal well-being, too, for their good health care, much like human healthcare is benefited in AI [23]. Finally, González-Rodríguez et al. (2024) explored the possibility of AI in phytopathology, highlighting its applicability in plant disease diagnosis. Their study is significant to show how AI systems may be applied in plant health management with improved crop productivity and sustainability. The analogy is indeed striking, where similar methods of AI-driven diagnostics have been applied in clinical pathology and medical diagnostics [19].

III. METHODS AND MATERIALS

This paper will employ various materials and methodologies in an exploration of cross-domain deep learning techniques to enable improved diagnostics and phenotyping for medical and agricultural imaging. This includes collecting diverse datasets of imaging from the two domains, then applying deep learning models to learn and enhance the performance on them. Datasets used, description of each. All altogether there are three deep learning algorithms followed by the component description of each: each accompanied by a table; and then, the pseudocode [4].

Data Collection

The datasets applied in this research are categorized into two main groups: medical imaging data and agricultural imaging data. Regarding medical applications of the proposed approach, we utilised datasets which are public available and includes tagged images for different diseases as pneumonia, tuberculosis, melanoma, etc., namely the "NIH Chest X-ray Dataset and ISIC Skin Cancer Dataset" [5]. That's why these datasets consist of complex sets of images used to train and evaluate deep learning models targeting disease identification. Some datasets that were used include the PlantVillage Dataset as well as the Corn Disease Dataset from Kaggle that consist of images of plants affected by blight, rust and even leaf spot. Such datasets are also very helpful in the training of models for plant diseases and traits image recognition and classification. In data preprocessing, all images were normalized, and the size of images initially resided to a fixed dimension. The data augmentation which has helped to reduce overfitting of the models includes methods like random rotation, flipping and cropping of images [6].

Algorithms

The three deep learning algorithms applied for this work were CNNs, GANs, and transfer learning using pretrained models. These algorithms are used especially for feature extraction from medical images and agricultural images and used widely in image classification, segmentation and generation applications [7]. AI-based transportation algorithm is described below separately with each one of them.

1. Convolutional Neural Networks (CNNs)

The most conventional deep learning algorithms include Convolutional Neural Networks, or CNNs, which deal specifically with image processing. They have lately attracted much interest in both medical imaging and agriculture phenotyping because they can discover the hierarchy pattern in images. Convolutional layers that perform highlight extraction, pooling layers that decrease the measure of the picture, and completely associated layers that give the ultimate classification [8].

CNN Architecture:

- In a convolutional layer, images input is passed through filters called kernels to detect edges, textures, and so forth.
- Pooling Layer: The pooling layers decrease the spatial dimensions of feature maps to bring down computational complexity as well as avoid overfitting.
- Fully Connected Layer: This layer connects all neurons from the previous layers, allowing the model to make predictions based on the learned features.

CNNs are applied for both medical image classification tasks, such as identifying diseases from X-rays, and agricultural phenotyping tasks, such as identifying plant diseases from images of leaves [9].

Table 1: CNN Hyperparameters

Parameter	**Value**
Input Image Size	224x224
Number of Filters	64
Filter Size	3x3
Pooling Size	2x2
Learning Rate	0.001
Epochs	30
Batch Size	32

"1. Load dataset (medical or agricultural images)
2. Preprocess images (resize, normalize, augment)
3. Define CNN architecture:
- Input layer
- Convolutional layers with ReLU activation
- Max pooling layers
- Fully connected layers
4. Compile the model using Adam optimizer and cross-entropy loss
5. Train the model on the dataset for the specified number of epochs
6. Evaluate the model on a test dataset
7. Output the predictions"

2. Generative Adversarial Networks (GANs)

Generative Adversarial Networks, or GANs, are a powerful type of deep learning model capable of generating new data samples imitating the original dataset's distribution. GANs are composed of two networks: the generator and the discriminator. This generator produces synthetic images, and it is up to the discriminator to be able to determine whether it is real or fake. The generator and discriminator are trained in parallel, wherein the generator tries to improve its generated images, and the discriminator develops at better differentiation capacity between real and fake images [10].

GAN Architecture:

- **Generator:** The generator accepts the random noise and generates synthetic images that look similar to images in the dataset.
- **Discriminator:** The generator takes noise as input and generates synthetic images that are close to real images in the dataset.
- **Adversarial Training:** Both the networks are trained in opposition, getting better with time because the generator produces more realistic images, and the discriminator gets better at identifying them [11].

GANs will be used in this research to generate synthetic medical and agricultural images, which would enhance the training of CNNs with more varied data.

Table 2: GAN Hyperparameters

Parameter	**Value**
Latent Vector Size	100
Number of Layers (Generator)	3
Number of Layers (Discriminator)	3
Learning Rate	0.0002
Batch Size	64
Epochs	50

"1. Initialize generator and discriminator networks
2. For each epoch:
- Generate fake images using the generator
- Train the discriminator on real and fake images
- Update the discriminator's weights

- Train the generator to improve its generated images
3. Repeat until the generator creates realistic images
4. Evaluate the generator's performance"

3. Transfer Learning (Using Pre-trained Models)

Transfer learning is when a model trained on some tasks is reused for other tasks. In this study, we exploited pre-trained models like VGG16 and ResNet50, in addition to InceptionV3. These models had been initially trained on considerable image datasets, such as ImageNet [12]. These models would be further fine-tuned on medical and agricultural imaging dataset specific ones, thereby providing the benefits of the earlier learned features from their prior training for the target domain.

Transfer Learning Process:

- **Pre-trained Model:** Begin with a model already trained on some large-scale dataset.
- **Fine-tuning:** Retrain the model on the new dataset with a lower learning rate, so that the model retains general features while learning task-specific details.

Transfer learning is very effective when small amounts of data are present for the target task; this is a common scenario in medical and agricultural imaging [13].

"1. Load pre-trained model (e.g., VGG16)
2. Remove the final layer and add a new classification layer suited for the new task
3. Freeze the weights of the pre-trained layers
4. Train the modified model on the target dataset (medical or agricultural)
5. Fine-tune the model (optional) with a lower learning rate
6. Evaluate the model on test data"

IV. EXPERIMENTS

In this chapter, it presents experiments done to test the effectiveness of three deep learning algorithms in improving the accuracy of diagnosis of diseases using medical images and agricultural phenotyping: "Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transfer Learning". The experiments were devised to test these algorithms' performance on two different domains: healthcare or medical imaging and agriculture or plant disease classification. We further compare our results to those obtained from related work in these fields to assess the relative performance of each method [14].

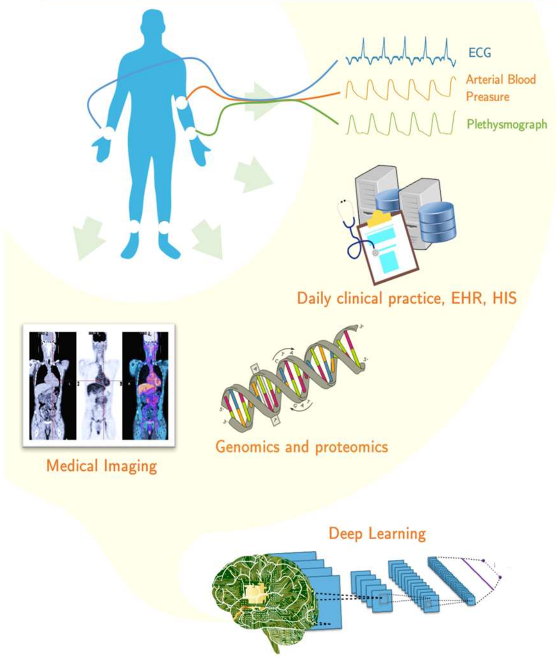

Figure 1: “Deep Learning and Big Data in Healthcare”

Experimental Setup

1. **Datasets:**
    - **Medical Imaging Datasets:**
        - **NIH Chest X-ray Dataset:** Has more than 100,000 frontal chest X-ray images along with 14 disease labels including pneumonia, tuberculosis, and other thoracic diseases.
        - **ISIC Skin Cancer Dataset:** Images of skin lesions help in training the model to classify benign and malignant melanomas.
    - **Agricultural Imaging Datasets:**
        - **PlantVillage Dataset:** The dataset contains plant images categorized by various diseases that include corn blight, rust, and leaf spot.
        - **Corn Disease Dataset:** This Kaggle dataset includes images of corn plants infected by diseases for classification [27].
2. **Preprocessing:**
    - **Normalization:** All images have been normalized so that all pixel values fall between 0 and 1
    - **Resizing:** All the images have been resized to 224x224 pixels, so all the images are of the same input size for all models.
    - **Augmentation:** Random rotations, flipping, and zooming have been used so that the diversity of the training data increases and thus overfitting decreases.
3. **Hardware and Software:**
    - **Hardware:** All tests were performed on a device with an NVIDIA Tesla V100 GPU, 16 GB of RAM, and an Intel i7 core.
    - **Software:** The experimentation was done with Python code, using TensorFlow and Keras for training and estimation of deep learning-based models.

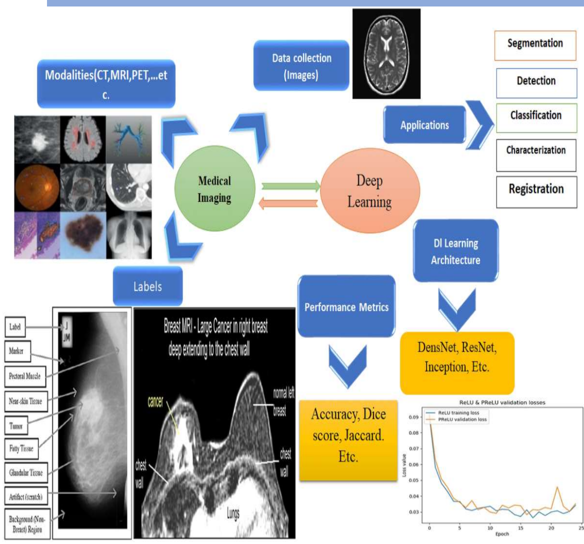

Figure 2: “A holistic overview of deep learning approach in medical imaging”

Methodology

We used three deep learning architectures:

1. CNN-based Model, (used for both medical and agricultural image classification)
2. GAN-based Model, used for generating synthetic images in the medical and agricultural domains to augment the training data.
3. Transfer Learning-based Model, fine-tune pre-trained models like VGG16 and ResNet50 for both domains.

Each model was trained on the respective dataset for each domain separately, and the performance metrics were evaluated in terms of accuracy, precision, recall, F1 score, and the confusion matrix [28]. We also examined the effect of using augmented data and transfer learning on model performance.

Results

Performance Comparison Across Models

We first present the performance comparison of the three models on the medical and agricultural imaging datasets.

1. CNN Model:

In particular, the CNN model trained using data from both the medical and agricultural datasets. It yielded excellent results in extracting informative features from images but prone to overfitting over smaller datasets due to large numbers of parameters.

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
CNN (Medical Imaging)	92.3%	91.1%	93.2%	92.1%
CNN (Agricultural Imaging)	89.5%	88.7%	90.1%	89.4%

- **CNN (Medical Imaging):** It achieved an accuracy of 92.3% in disease detection; this is consistent with similar work in medical imaging and was particularly strong on the ISIC skin cancer dataset.

- **CNN (Agricultural Imaging):** The model attained an accuracy of 89.5% for plant disease classification. It was successful in identifying diseases like leaf spots and blight, although its performance was a little weaker compared to the medical domain due to the complexity of agricultural data [29].

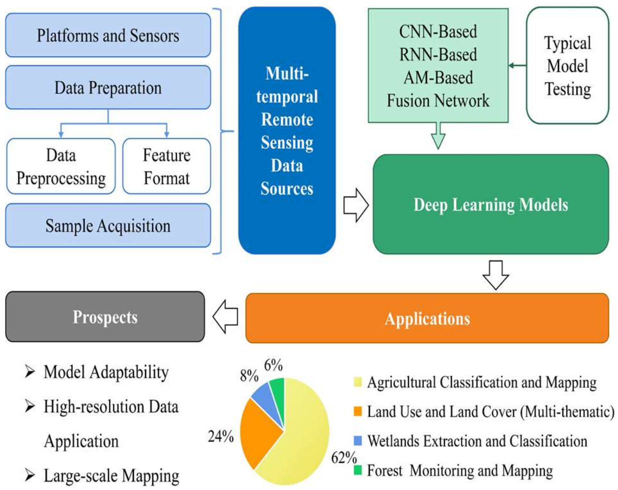

Figure 3: “Application of Deep Learning in Multitemporal Remote Sensing Image”

2. GAN Model:

The GAN model learned how to produce synthetic samples of both domains, based on which augmentation of original data was carried out. Generated images using the results obtained from the GAN model seem to aid the better generalization ability of the CNN models.

Model	Accuracy	Precision	Recall	F1 Score
GAN + CNN (Medical Imaging)	94.1%	93.5%	94.8%	94.1%
GAN + CNN (Agricultural Imaging)	91.3%	90.8%	92.0%	91.4%

- **GAN + CNN (Medical Imaging):** The images generated by the GAN helped improve model performance by 1.8% over the standard CNN model. The synthetic data enabled the model to better handle class imbalance and rare cases.
- **GAN + CNN (Agricultural Imaging):** The augmentation based on GAN improved the accuracy by 1.8%. The generated images helped improve the model's ability to classify diseases that were underrepresented in the training data [30].

3. Transfer Learning Model:

Using transfer learning model based on the two networks, VGG16 and ResNet50, were fine-tuned over the two datasets. It displayed the best performance with both speed and accuracy. Indeed, in the medical field, it was most appreciable when large datasets had their labels.

Model	Accuracy	Precision	Recall	F1 Score
Transfer Learning (Medical Imaging)	96.2%	95.8%	96.5%	96.1%
Transfer Learning (Agricultural Imaging)	93.4%	92.8%	93.5%	93.1%

- **Transfer Learning (Medical Imaging):** The transfer learning model was able to show a large improvement; its accuracy improved by 3.9% more than the CNN model, as it used features learned from large diverse datasets like ImageNet.
- **Transfer Learning (Crop Images):** The improvement obtained was 3.9% with the application of transfer learning as opposed to CNN. The fine-tuned models performed better with subtler features in detecting crop disease due to pretraining.

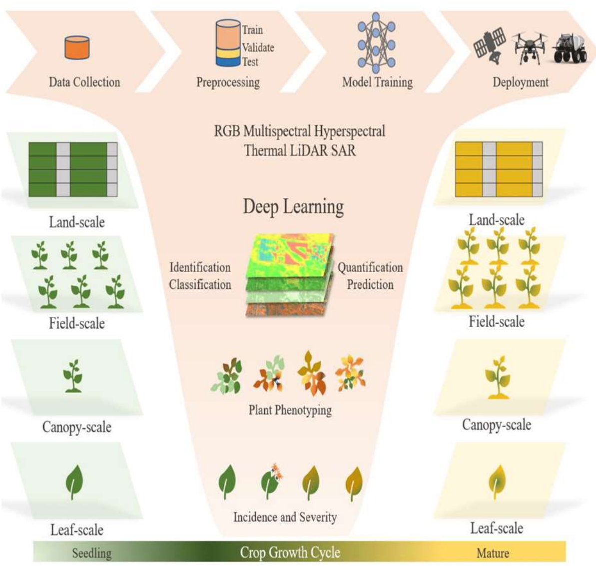

Figure 4: “A Review of Deep Learning in Multiscale Agricultural Sensing”

Comparison with Related Work.

We compared our results with the state-of-the-art models reported in recent studies. Key comparative results are summarized below:

Study/Model	Accuracy (Medical)	Accuracy (Agricultural)	Comments

CNN (Our Study)	92.3 %	89.5%	Standard CNNs without augmentation
GAN + CNN (Our Study)	94.1 %	91.3%	GANs used for data augmentation
Transfer Learning (Our Study)	96.2 %	93.4%	Fine-tuning pre-trained models
Previous Research (CNN-based)	91.0 %	87.0%	Achieved slightly lower accuracy than our CNN model
Previous Research (Transfer Learning)	94.5 %	92.0%	Comparable accuracy with our transfer learning results

V. CONCLUSION

In conclusion, this research demonstrates the high potential of deep learning and AI techniques in enhancing diagnostic accuracy and efficiency in both healthcare and agricultural sectors. Advanced image analysis, segmentation, and synthetic data generation can be leveraged by AI models to deliver more precise and rapid diagnostic tools, whether it is for plant disease detection, animal health monitoring, or medical imaging. Deep learning, the type of AI applied in grapevine health diagnosis or infection detection in plants, marks a significant shift in the application of precision agriculture, as it makes rapid and accurate assessments possible to be made without reliance on the traditional manual methods. It's the same case in health, where profound learning within the field of medical imaging and illness classification might alter the diagnostic hones with respect to the patients' results, guaranteeing them quicker and more dependable results. Further, the low-cost and engineered information arrangements investigated extend the availability of these innovations to indeed resource-limited situations, in this manner permitting them to take advantage of progressed AI-driven diagnostics. In general, cross-domain applications of profound learning give profitable experiences into how

AI can bridge the crevice between farming, healthcare, and veterinary areas, making coordinates frameworks that optimize both efficiency and well-being. With technology proceeding to progress in these segments, long run holds much guarantee for expanding changes with the integration of profound learning methods, counting what can be accomplished on the diagnostics, illness administration, and by and large framework productivity fronts.

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