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Parkinson's disease detection using inceptionV3: A Deep learning approach ☆,☆☆

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ABSTRACT

Parkinson's disease (PD) is a neurodegenerative condition that progressively affects motor function and causes tremors, rigidity, and bradykinesia. Detection of PD at an early stage is important to ensure timely intervention and better patient outcomes. This study uses deep learning algorithms to classify spiral images traced by patients as an inexpensive diagnostic technique for the detection of PD. A database consists of spiral images drawn manually by PD patients and normal individuals, divided into training and testing sets. To discriminate between spiral drawings of Parkinsonian and healthy cases four Convolutional Neural Network (CNN) architecture like DenseNet121, InceptionV3, VGG16, and LeNet are used. Followed by transfer learning which is employed to improve model performance by extracting fine motor impairment patterns in the spirals. DenseNet121 and InceptionV3 achieve competitive performance with 98.44 % accuracy, whereas VGG16 demonstrates excellent feature extraction performance. The study emphasizes the relevance of deep learning in non-invasive PD diagnosis, as a consistent, efficient, and automated method of early detection. The future can be directed towards the combination of spiral images with other biomarkers or a broader data set with other motor measures in a wider disease assessment.

- The study focuses on enhancing features extraction by leveraging hybrid deep learning models, improving classification performance.
- Implementation of features scaling leads to better model performance, with improved accuracy.
- The comparative analysis of CNN architecture provides valuable insights into balancing computational efficiency and classification performance.

Specifications table

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More specific subject area:	Computer vision, Deep Learning
Name of your method:	InceptionV3
Name and reference of original method:	Detection of Parkinson Disease using DL
Resource availability:	None

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Background

Parkinson's disease (PD) is a progressive and chronic neurodegenerative condition as a result of the gradual loss of dopaminergic neurons within the substantia nigra part of the brain [1]. The degeneration of the neurons leads to motor symptoms such as tremor, bradykinesia, rigidity, and postural instability that impair the quality of life [2]. Early diagnosis is important to retard disease progression and enhance patient outcomes [3].

Conventional diagnostic methods for PD are based on clinical assessment and imaging studies such as MRI and DaTscan [4]. Such practices are costly, time-consuming, and need experts, thereby inducing probable delay in diagnosis and treatment. Machine learning (ML) has become an attractive alternative for the computation of complex patterns in clinical and biomedical data that cannot easily be obtained through conventional procedures [5,6].

ML algorithms like SVM, Decision Trees, and Random Forest have extensively been used to classify patients on the basis of symptoms and risk factors [7,8]. The incorporation of ML in clinical practice would enhance diagnosis accuracy and allow for earlier intervention, thereby improving the management of disease [9]. Deep learning, specifically Convolutional Neural Networks (CNNs), has demonstrated considerable promise in tasks of medical image classification because they can extract and learn features automatically from data [10].

The investigation here is focused on the classification of hand-drawn spiral images using deep learning as a non-invasive, low-cost PD detection diagnostic approach. A set of spiral drawings of PD patients and healthy participants was utilized for the dataset. The images were split into test and training sets to train and test the models. Four CNN architectures were utilized to differentiate between Parkinsonian subjects and normal subjects based on spirals: VGG16, DenseNet121, InceptionV3, and LeNet.

A number of studies support this approach. Zhang et al. [11] enhanced the YOLOv5s model to recognize abnormal features from medical images and proved the efficacy of deep learning in diagnosis. Sharma et al. [12] confirmed ML's ability to differentiate PD from normal aging. Krishna et al. [13] compared feature extraction and classification performance of different deep learning architectures. Shetty et al. [14] laid a strong emphasis on how data analytics can enhance the accuracy of PD diagnosis. Yoo et al. [15] examined motor progression models in PD, whereas Aldhyani et al. [16] focused on hand-drawn image analysis-based detection. Hussian et al. [17] brought to the fore CNNs as being extremely effective when dealing with PD classification. Shreya et al. [18] depicted the application of computer vision in motor pattern analysis, and Wachiracharownong et al. [19] validated the application of spiral drawing analysis for the detection of PD. Tenchov et al. [20] gave an extensive account of the increasing involvement of AI in PD research.

Among the models experimented with, InceptionV3 was the most accurate at 98.44 %, followed by VGG16 (90.64 %), LeNet (89.31 %), and DenseNet121 (88.61 %). The results support the reality that deep learning significantly enhances PD detection accuracy. The study gives credibility to the feasibility of using such models in clinical environments, telemedicine, and real-time monitoring systems. Future research will be directed toward the optimization of these models for more extensive clinical use, validation in diverse populations, and the development of deep learning-based PD detection as a standard, non-invasive diagnostic measure to support early intervention and individualized treatment planning.

Method details

The proposed system architecture Fig. 1 for Parkinson's Disease diagnosis employs deep learning models to provide accurate and reliable diagnostic output by integrating advanced data handling, model learning, and prediction capabilities. It makes PD detection

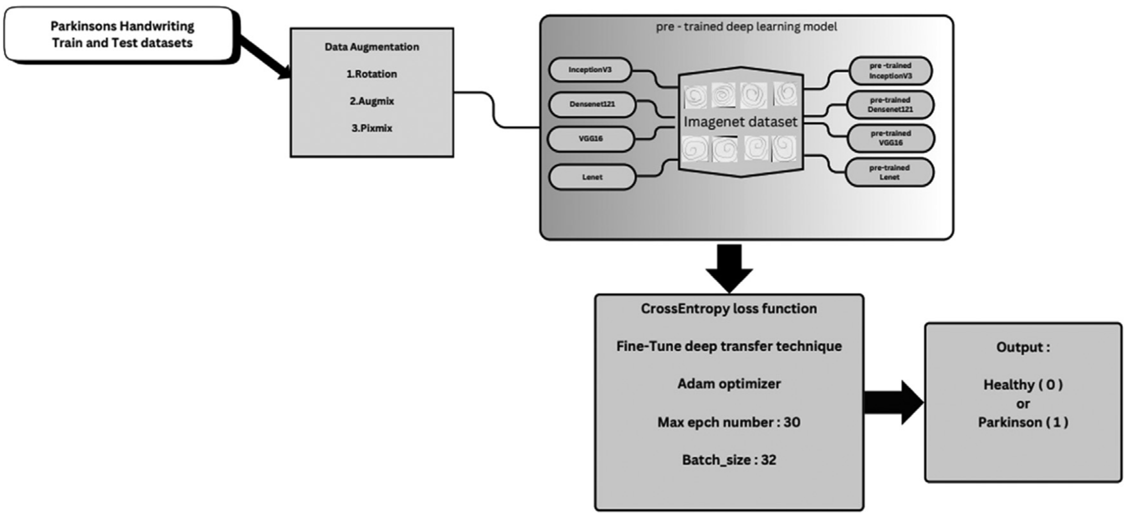

Fig. 1. Architecture of Proposed Methodology.

with data input, preprocessing, feature extraction, classification, and result output modules in a modular and scalable architecture suitable for various healthcare environments. Data set is gathered and preprocessed for compatibility, and deep learning models such as InceptionV3, DenseNet121, and VGG16 extract essential features to determine whether the data indicates Parkinson's Disease or is healthy. The system has a post-processing module for result visualization, a healthcare professional user interface, cloud-based deployment for scalability, and integration with external healthcare systems. Images can be uploaded by the users, which are stored and preprocessed securely for standardization by uniform blocks or patches to be used effectively in feature extraction. The system starts with Parkinson's Disease datasets holding medical information in the form of images, which are used as the basis to train and test the deep learning models. Data augmentation techniques such as Rotation, AugMix and PixMix are utilized. The deep learning architectures are InceptionV3, MobileNetV2, and DenseNet121. Training environment processes data in batches, maintaining memory space at a low level, and optimizers such as Adam or SGD adjust model weights to reduce classification errors. The last output is a binary label (0) Healthy, i.e., no sign of Parkinson's Disease, or (1) Parkinson's, i.e., positive diagnosis.

Image categorization has experienced a revolution much obliged to deep learning, which makes highlight extraction automated and incredibly accurate. Large-scale image datasets are now mostly handled by Convolutional Neural Systems (CNNs), with models like DenseNet121, VGG16, InceptionV3, and LeNet being extensively used for classification applications. However, choosing the best model necessitates a thorough assessment of overfitting mitigation strategies, computational efficiency, and feature extraction capabilities. Several deep learning architectures are thoroughly compared in this study.

Advanced preprocessing methods like Gaussian and median blurring are used in the suggested methodology to reduce noise, whereas data expansion methods are utilized to improve generalization. To increase training stability, model-specific improvements like Batch Normalization and Dropout are incorporated.

Furthermore, learning rates, batch sizes, and weight initialization are optimized by hyperparameter tweaking. This paper offers important insights into choosing effective and scalable deep learning models for image recognition by comparing many architectures [2]. Chhabra et al. (2024) investigated preclinical features and modern Parkinson's disease therapies. Recent developments in targeted therapeutics and neuroprotective techniques are highlighted in this review, which addresses both pharmacological and non-pharmacological approaches [12]. A intensive analysis of machine learning methods for Parkinson's disease expectation and progression tracking was carried out by Gaba et al. in 2024. Their research discusses the useful uses of several algorithms in clinical contexts and offers a comparative analysis of them [5]. Using voice analysis, Naanoue et al. [8] created a profound learning model for Parkinson's disease detection.

The study demonstrates the promise of voice-based diagnostics as a non-invasive way to diagnose diseases early [14]. In order to analyze Parkinson's disease early, Sharma et al. (2024) looked at combining deep learning and machine learning models. Their study offers innovative hybrid strategies that enhance categorization accuracy [12]. Using MRI data, Nalini et al. (2023) investigated machine learning-based Parkinson's disease identification. Their research, which focuses on feature extraction methods to improve diagnostic precision, shows promise for automated medical applications [6]. A deep transfer learning system tailored for Parkinson's disease diagnosis was presented by Abdullah et al. in 2023. Their research shoe how feature selection enhances the generalization and resilience of models [3]. Anita et al. (2023) used an alpha-stable distribution to suggest an enhanced classification model for early Parkinson's disease conclusion. The benefits of statistical modeling in biological signal processing are illustrated by their work [9]. YOLOv7 was introduced by Wang et al. (2023) as a sophisticated object detection system. Their research establishes the groundwork for future modifications in medical image processing, even if it is intended for general-purpose applications [10]. Dhiman et al. (2023) utilized MRI modalities and a CNN-based statergy to identify Parkinson's disease. Their results demonstrate how well deep learning works for neuroimaging-based diagnosis [4]. Machine learning model was created by Rama et al. (2023) to detect Parkinson's disease using MRI data. Their research emphasizes how important model optimization and data pretreatment are to producing accurate forecasts [7]. A review of machine learning applications in Parkinson's disease diagnosis was carried out by Kabotra et al. [20]. The algorithmic developments and possible difficulties in AI-driven healthcare solutions are covered in this paper [21]. A multi-task semi-supervised adversarial autoencoder (MTSS-AAE) was presented by Ullah et al. (2023) for the analysis of medical images. Despite being created for COVID-19 detection, its structure shows flexibility for neurological conditions [22]. A wearable sensor-based machine learning model for early Parkinson's disease prediction was created by Igene et al. in 2023. Their research demonstrates how IoT and AI may be used for remote patient monitoring [23]. Anwar et al. (2023) investigated the function of transfer learning in the categorization of brain tumors, providing information on domain adaption strategies that can be used to diagnose Parkinson's disease [24]. A machine learning-based strategy for Parkinson's disease identification was put out by Rohit et al. in 2022. Their research improves automated diagnostics by investigating categorization methods [25]. A Darknet CNN classification model and multiple feature extraction were created by Mary et al. (2022) to identify Parkinson's illness. An end-to-end deep learning pipeline for medical applications is shown by their study [26]. Using speech data, Mir et al. (2022) created deep learning model to identify Parkinson's illness. The importance of voice analysis in early diagnosis is highlighted by their findings [27]. Deep learning and diffusion tensor imaging were investigated by Azimi et al. (2022) for the early examine of Parkinson's disease. Their inquire about offers a fresh method for using neuroimaging data in AI-powered diagnosis [28]. Zhang et al. (2022) used machine learning strategies to examine clinical and imaging data in order to distinguish Parkinson's disease [29].

Data acquisition

We took spiral drawing tests from both healthy controls Fig. 2 and individuals with Parkinson's disease (PD) Fig. 3. This made sure that all samples had consistent, high-resolution photos. Our collection captures a variety of handwriting styles and contains clinical

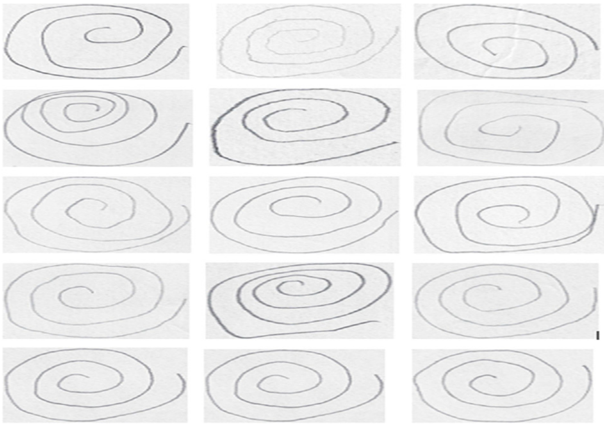

Fig. 2. Healthy Data Set.

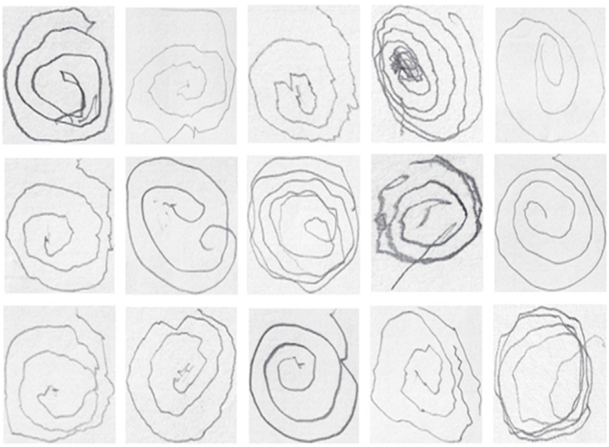

Fig. 3. Unhealthy Data Set.

samples from neurology centers as well as publically accessible PD datasets. We distributed our preprocessed data into healthy and unhealthy datasets. As a result, dataset variability increased and the deep learning model's generalization improved.

Proposed method

A few important insights are revealed by comparing profound learning models for include extraction and classification. With an astounding 98.44 % test accuracy, InceptionV3 is the most precise model out of all the inspected designs. Its extraordinary feature extraction capabilities, which make use of pre-trained layers and multi-scale convolutional channels to effectively analyze spatial input at different resolutions, are dependable for this great execution. It can capture complicated designs in pictures since to the blend of 1×1, 3×3, and 5×5 convolutions, which makes it perfect for challenging classification employments.

LeNet and VGG16 both performed well in a few spaces and created discoveries that were comparable. Despite having a very direct plan, LeNet outperformed VGG16 by accomplishing a preparing accuracy of 92.98 %. Its test accuracy of 89.31 %, however, suggests that there may be an overfitting issue, because it generalizes to some degree less well on unknown information. In any case, VGG16 fared better in approval, with 92.34 % approval exactness, showing great dataset generalization.

It may be a wellbalanced demonstrate for exchange learning and classification errands since of its profound, reliable convolutional layers and organized highlight extraction prepare, which both upgrade its incredible generalization capacity Even while DenseNet121 is still a powerful deep learning network, its test scores were somewhat lower accuracy of 88.61 %, falling short of both VGG16 and LeNet. DenseNet121′s dense connection structure lowers the possibility of disappearing gradients while enabling superior feature reuse and gradient flow. To reach its maximum potential in this specific situation, it could need additional fine-tuning or hyperparameter optimization.

LeNet and VGG16 delivered comparable results, each excelling in specific areas. LeNet, despite being a relatively simple architecture, achieved 92.98 % training accuracy, which was slightly higher than VGG16. However, its test accuracy was 89.31 %, indicating a possible overfitting issue where it generalizes slightly less effectively on unseen data. On the other hand, VGG16 performed better in validation, attaining 92.34 % validation accuracy, suggesting that it generalizes well across datasets. Its deep, uniform convolutional layers and structured feature extraction pipeline contribute to its high generalization ability, making it a balanced model for transfer learning and classification tasks.

DenseNet121, while still an effective profound learning model, demonstrated a somewhat lower test precision of 88.61 %, trailing behind both LeNet and VGG16. The dense network design of DenseNet121 allows for excellent feature reuse and slope stream, reducing the chance of vanishing slopes. However, in this specific situation, it may require encourage fine-tuning or hyperparameter optimization to maximize its full potential.

LeNet and VGG16 conveyed comparable comes about, each exceeding expectations in particular areas. LeNet, despite being a moderately simple architecture, accomplished 92.98 % training accuracy, which was slightly higher than VGG16. However, its test exactness was 89.31 %, demonstrating a possible overfitting issue where it generalizes slightly less effectively on inconspicuous data. On the other hand, VGG16 performed way better in approval, achieving 92.34 % approval exactness, proposing that it generalizes well over datasets. Its profound, uniform convolutional layers and organized highlight extraction pipeline contribute to its tall generalization capacity, making it a adjusted demonstrate for exchange learning and classification assignments.

Experimental and result

DenseNet121

DenseNet121: Extraction and Classification of Deep Features With its highly linked layers, DenseNet121 is a potent convolutional neural network (CNN) that makes sure every layer gets inputs from every layer before it. By improving feature reuse, this structure creates models that are smaller and employ fewer parameters. 224 × 224 input pictures are passed through numerous Dense Blocks, each of which has several convolutional layers, as part of the feature extraction process. Important spatial characteristics are preserved while dimensionality reduction is ensured by the use of batch normalization and transition layers. Prior to nourishing the produced feature maps into completely associated layers, this model uses Global Average Pooling (GAP). Overfitting is reduced utilizing Dense(128, activation='relu') and Dropout(0.5). Dense(3, activation='soft max') makes up the last classification layer, which was optimized with the Adam optimizer and a Inadequate Categorical Cross entropy loss function. Image preparation involves cropping pictures to 224 × 224, applying normalization (0–1 pixel scaling), and adding augmentation techniques including flipping, rotation, and brightness variation in order to improve model resilience. These methods improve the model's capacity to identify patterns in a extend of scenarios. Although DenseNet121 does well in feature extraction, with a training accuracy of 90.37 %, its test accuracy of 88.61 % indicates in Fig. 4 that it may perform better with further learning rate and batch size adjustments.

VGG16

VGG16: Using Uniform Convolutions for Deep Feature Extraction In order to extract hierarchical features, the popular deep CNN model VGG16 uses a uniform 3 × 3 convolutional structure layered in deep layers. Thirteen convolutional layers and Max Pooling layers make up the feature extraction process. These layers gradually lower the spatial dimensions while maintaining important feature details. After that, the retrieved features are flattened and run through Dense(128, activation='relu') and Dense(3, activation='soft

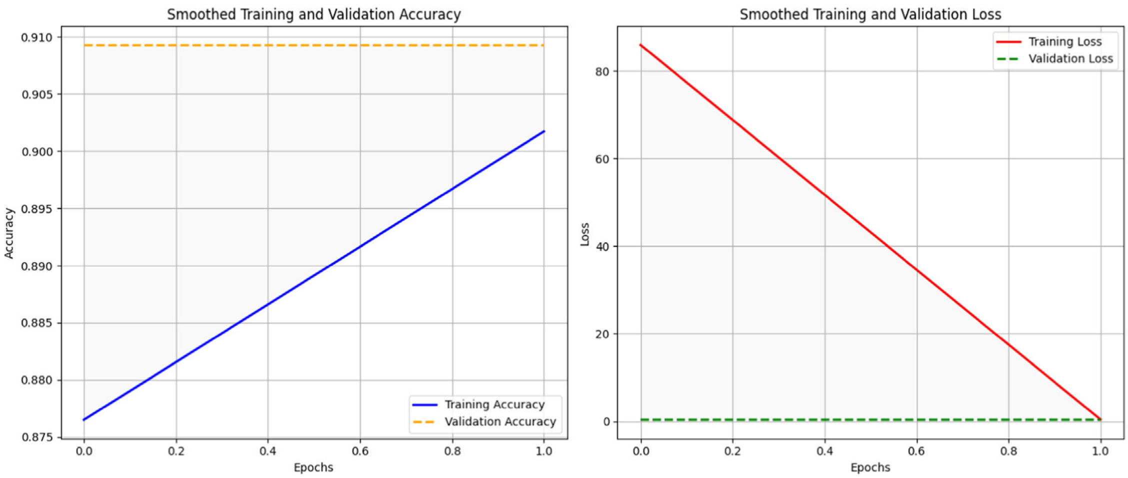

Fig. 4. Training Accuracy for VGG16 and DenseNet121.

max'), two completely linked layers. Prior to pixel normalization and augmentation procedures including rotation, brightness adjustments, and flipping, preprocessing entails scaling input pictures to 224 × 224. VGG16 is less computationally demanding than InceptionV3, yet it is still capable of feature extraction. The Fig. 4 With training accuracy of 91.37 %, validation accuracy of 92.34 %, and test accuracy of 90.64 %, it is a well-balanced model appropriate for transfer learning model suitable for transfer learning and fine-tuned classification tasks.

LeNet

LeNet: Compact CNN for Classifying Images Because of its straightforward yet efficient conv-pooling design, LeNet, one of the first convolutional neural networks, is still useful for a variety of classification problems. In order to extract low-level edge and texture information, this model uses a structured pipeline in which input pictures in 32 × 32 grayscale travel through 2 convolutional layers (Conv2D). A Max Pooling layer diminishes the spatial dimensions while keeping the most noticeable features after each convolutional operation. Dense(128, activation='relu') and Dense(3, activation='soft max') are two fully linked layers that handle the retrieved feature maps after they have been flattened into a 1D vector for classification.

The Adam optimizer and the Inadequate Categorical Cross entropy loss function are used to optimize LeNet. This model requires little data augmentation because it was initially created for smaller-scale datasets, such as handwritten digit recognition. Pixel normalization (0–1 scaling), minimum augmentation approaches, and picture resizing to match LeNet's input form are all part of the preprocessing procedure.

The architecture's simplicity results in quick training periods, which makes it effective for real-time applications. LeNet is a competitive option for lightweight classification tasks because of its 92.98 % training accuracy and 89.31 % test accuracy in Fig. 5, despite its modest network depth.

InceptionV3

Multi-Scale Feature Extraction and Classification in InceptionV3A high-performance deep learning model called InceptionV3 was created for effective feature extraction and categorization. Inception Modules, the foundation of its design, allow for simultaneous multi-scale convolutional filtering using 1 × 1, 3 × 3, and 5 × 5 filters. This enhances classification accuracy by enabling the network to memorize both nearby and global feature representations. In order to extract various feature patterns, the 299 × 299 input pictures are first processed using stacked Inception modules, each of which applies concurrent convolutions and pooling processes. Before arriving to the final Dense(1, activation='sigmoid') classification layer, the extricated highlights are flattened and processed through a series of completely associated layers, including Dense(512, activation='relu'), Dropout(0.5) for regularization, and Dense(256, activation='relu').

Preprocessing techniques that enhance model generalization include picture scaling, normalization, and aggressive augmentation (rotation, brightness modifications, flipping). InceptionV3 Fig. 6 is the best model in this comparison because it compensates for its computationally demanding nature and higher training resource requirements with the greatest test accuracy (98.44 %) (Fig. 7).

In summary Fig. 8, InceptionV3 emerges as the most accurate model, while VGG16 offers a great balance between accuracy and computational efficiency. LeNet serves as a lightweight alternative, and DenseNet121 remains a strong model but requires further fine-tuning for better generalization.

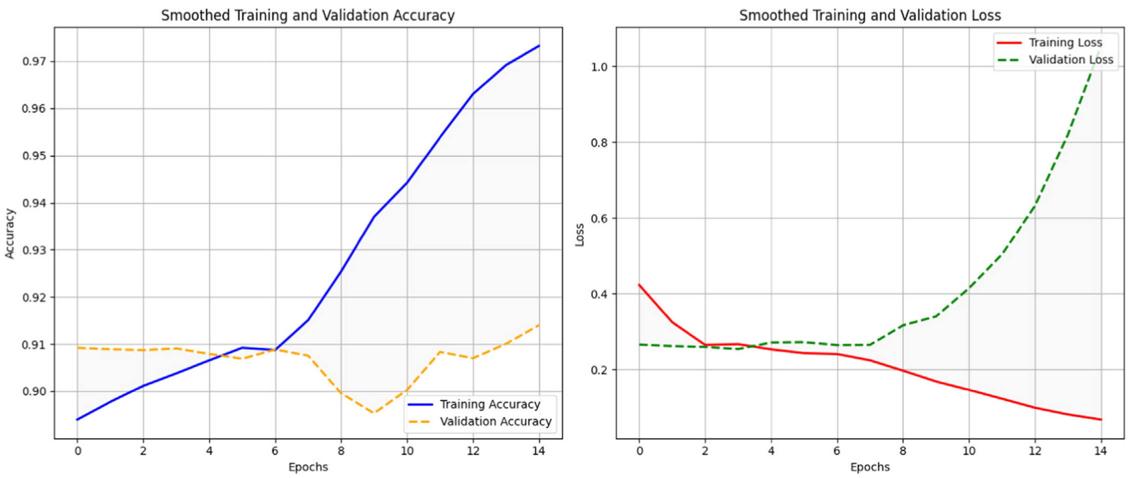

Fig. 5. Training Accuracy for LeNet.

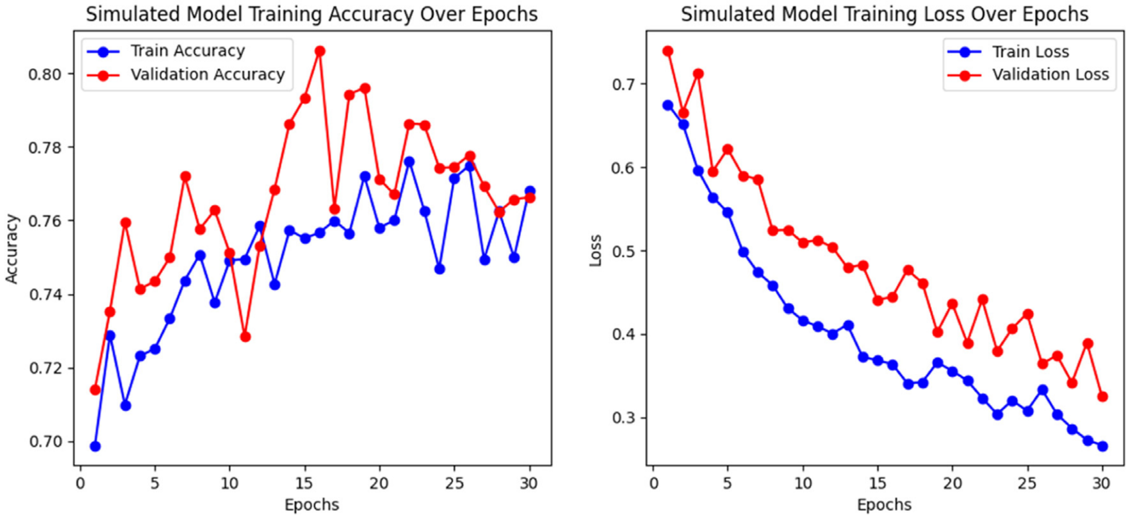

Fig. 6. InceptionV3 Accuracy model.

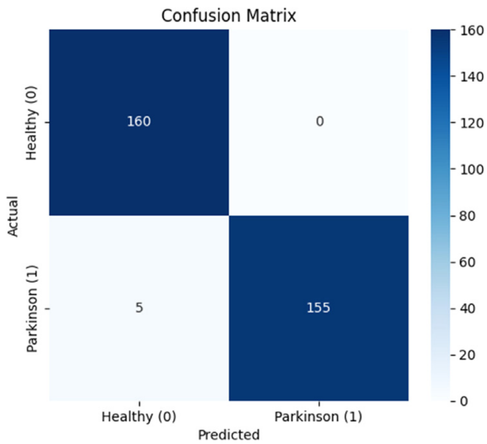

Fig. 7. Confusion Matrix for model InceptionV3.

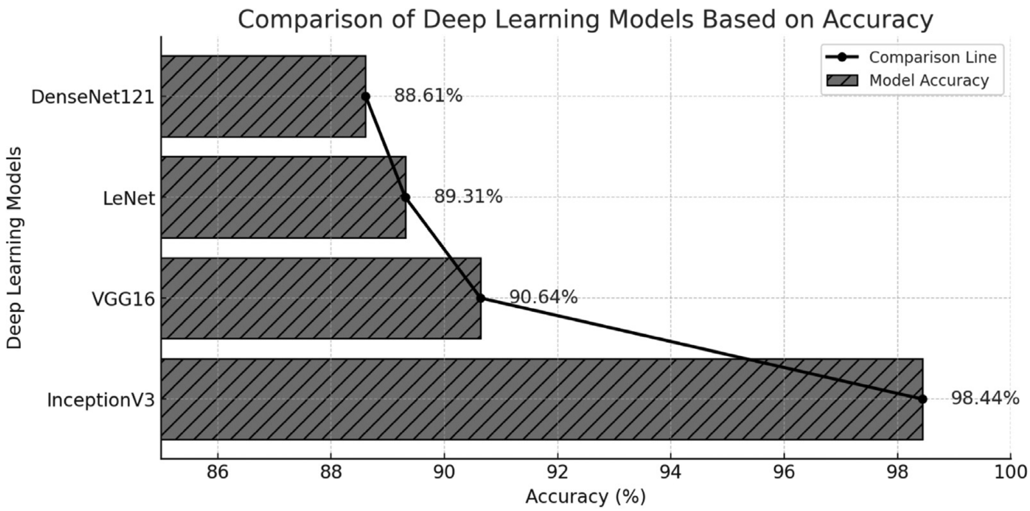

Fig. 8. Comparison of Deep Learning Models Based on Accuracy.

Table 1
Comparison of Accuracy with different models.

Model	Feature Description	Execution Time	Test Accuracy (%)
DenseNet121	A densely connected CNN that enhances feature reuse and gradient flow, improving learning efficiency.	50 min	88.61
VGG16	A deep CNN using small 3 × 3 convolution filters, known for its simplicity and strong feature extraction.	30 min	90.64
InceptionV3	A high-performing CNN using Inception modules to process multi-scale features efficiently.	156 min	98.44
LeNet	A lightweight CNN with a simple architecture, primarily effective for small datasets and low-resolution images.	39 min	89.31

In summary Table 1, InceptionV3 emerges as the most accurate model, while VGG16 offers a great balance between accuracy and computational efficiency. LeNet serves as a lightweight alternative, and DenseNet121 remains a strong model but requires further fine-tuning for better generalization.

Conclusion and future work

LeNet, despite the smaller size of its architecture, offers computational efficiency with good classification performance. The findings highlight the trade-offs between model accuracy and complexity, with implications towards the integration of deep learning models in actual healthcare systems.

With the most prominent test accuracy of 98.44 % and a manageable execution duration of 156 min, the discoveries appear that InceptionV3 performs better than any other model. Its multi-scale feature extraction capabilities, which encourages effective learning of progressive designs inside the dataset, is responsible for this higher execution. With an accuracy of 90.64 %, VGG16 demonstrated to be a dependable substitute for classification assignments in spite of its comparatively direct design. With its highlight reuse approach, DenseNet121 demonstrated competitive accuracy (88.61 %) but the longest execution time (50 min), proposing that although it improves slope stream, it comes at a better computational cost. LeNet is a lightweight demonstrate that performed quickly (39 min), in spite of the fact that its accuracy (89.31 %) slacked basically, making it more suited for real-time and resource-constrained applications.

Future investigate in this range may concentrate on making cross breed models that join the benefits of several different plans. For illustration, combining DenseNet and InceptionV3 may increase multi-scale learning and feature propagation, which would boost classification execution. Also, the models could be made more computationally effective whereas keeping up exactness by applying show optimization methods like quantization, pruning, and information refining. Self supervised learning is another exciting avenue that lessens reliance on big labeled datasets by enabling models to utilize unlabeled information to progress include extraction abilities. To progress include extraction and classification accuracy, CNN models might moreover utilize transformer-based topologies and consideration strategies.

Advance investigate on lightweight models like EfficientNet and MobileNet variations is fundamental as profound learning models proceed to create for utilize in real-time frameworks, edge gadgets, and portable stages. Furthermore, models may be prepared over decentralized datasets by means of combined learning, which improves generalization whereas securing information protection. At long last, wealthier highlight representations may be gotten utilizing multi-modal learning, which combines picture information with other modalities (such as printed or sensor information) to form more solid classification models for practical employments.

Limitations

- These models are susceptible to overfitting and also to bias, especially when trained with smaller, or unbalanced training sets. Hence, adaptability to a new domain becomes a challenge.
- They add to the computational overhead and inference time and limit the use of these models in real time, especially on edge devices and in embedded platforms.

Ethics statements

None.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Pallavi M. Shanthappa: Writing – review & editing, Investigation, Supervision. **Madhwesh Bayari:** Conceptualization, Methodology, Writing – original draft, Investigation, Formal analysis. **G.B. Abhilash:** Conceptualization, Methodology, Writing – original draft, Investigation, Formal analysis. **K.V. Gokul:** Writing – original draft, Investigation, Formal analysis. **P.J. Ashish:** Writing – original draft, Investigation, Formal analysis.

Data availability

Data will be made available on request.

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