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A hybrid deep unified model on diverse datasets

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Abstract

Deep learning is very efficient in image classification, but the classical feature extraction algorithms are understandable and robust. The categorization of images serves as a foundation for diagnosing, planning treatment, and analyzing images. Powerful algorithms handle various types of data effectively, emphasizing the importance of robust and understandable methods in the field of image processing. The HDUM designed in the present study combines ResNet, DenseNet, and InceptionNet deep learning methods. The first step is in image classification, which identifies high-level features in the raw images by picking up local and global patterns. Furthermore, HDUM uses classical techniques of feature extraction to obtain auxiliary information. Additionally, the fused features are given to a classifier to generate an effective final classification. The model constitutes a unique attention mechanism whereby resources are allocated dynamically with attention depend on salient parts of images to be processed. The single design of HDUM that incorporates different types of data sets and at the same time guarantees interpretability and performance makes it stand out from the rest. Based on various research studies conducted on standard datasets, HDUM is the most suitable technique regarding accuracy in classification, ease of use, and data heterogeneity. This comparison attributes HDUM to CNNs, ResNet, DenseNet, InceptionNet, VGG16, and the hybrid CNN model, showing superior results in various performance metrics. HDUM excels in practical applications due to its superior generalizability and resilience to input data changes. This study improves the classification

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of pictures using a combination of deep learning and classical feature extraction methods by exploiting the beneficial synergistic im-pact of the implemented strategies.

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1. Introduction

Complexity and variance make picture classification difficult for computer vision. These anatomical features and imaging anomalies make traditional categorization difficult. Image datasets with low sample counts, class imbalances, and noisy annotations may impede deep learning model training. Hybrid deep learning architectures, unified frameworks, and improved data augmentation are needed. Picture categorization systems benefit from these tactics because they increase their accuracy and generalizability. Segmentation, classification, and computer vision in pictures have all been enhanced by deep learning. In order to automatically learn how to identify images, CNNs automatically extract vast amounts of visual data. There are performance and accuracy issues with image recognition and categorization. The HDUM uses advanced picture categorization algorithms, such as ResNet, DenseNet, and InceptionNet, which are deep learning architectures. A combination of ResNet depth, DenseNet dense connectivity, and Inception-Net's multiscale feature extraction is what makes up the HDUM. The model lines up with the categorization of the images. Image classification becomes more complicated with computer vision. To improve image analysis and manipulation, hybrid algorithms combine methods. Hybrid algorithms use contemporary statistical models, machine learning and traditional methods. Com-plicated image data is handled by HDUM algorithms allowing the use of advanced processing and analysis. Also, it is possible to correct the flaws of approaches and capitalize on strengths through the complementary tactics. HDUM enhances the accuracy of challenging sceneries. ResNet, DenseNet, and InceptionNet are effective photo categorization models but have drawbacks. Complex models such as DenseNet and InceptionNet make it challenging to grasp how attributes affect classification. These models may have trouble generalizing to images from other sources or modalities. Even with transfer learning, deep learning models may fail with data distributions very different from those of the training data. Finally, these models may ignore context and spatial links. DenseNet quickly obtains local data through dense connections, but it may miss context. Healthcare-specific deep learning model research must be inventive to overcome these constraints. To overcome these limitations, future medical image analysis algorithms will rely completely on deep learning. Improving domain knowledge, interpretability, and generalization works. Image analysis must be accurate and swift to improve the results. This requirement led to the construction of the HDUM for enhanced image classification, which integrates ResNet, DenseNet, and InceptionNet. The model employs a variety of designs to make use of these architectures complemented multiscale properties, depth, and dense connections. The hybrid approach increases the resilience of the model, its generalizability, and picture property extraction. The HDUM would modify classification of images. With this technology, healthcare givers are able to make informed choices. This is not to claim to be superior by any chance but to explore the possibility of a hybrid approach to eliminate the issues of interpretability and generalizability and achieve better classification rates on various datasets. Through this approach, the study aims to provide both a practical solution and insights into the broader direction of hybrid model development in deep learning. Section 2 about the related work. Section 3 outlines the steps for the hybrid model. Section 4 covers dataset utilization, and image processing. Section 5 describes the implementation of the HDUM. Section 6 present a comparison with other models, and Section 7 the conclusions.

2. Related Work

This section reviewed related works that explored image classification, segmentation, and deep learning models in various applications. Seethalakshmy et al. [1] developed a framework using DCNNs, VGG16 and ResNet50, for the classification from CT scans with transfer learning in medical diagnostics. Gupta, Jain, and Kumar [2] analyzed the efficacy of MobileNetV2 and EfficientNet-B0 for object detection in thermal images with higher accuracy. Mounika, Reddy, and Ramakrishnaiah [3] enhanced feature representation by integrating the CBAM with ResNet-50, which allowed the model to prioritize informative spatial regions effectively. Similarly, Bhagirath, Bhatnagar, and Raja [4] explored the use of bio-inspired algorithms to fine-tune CNN hyperparameters for agricultural image analysis. Then, Sawale et al. [5] emphasized the ethical and practical implications of deploying these deep learning models in drug discovery. Almotiri et al. [6] examined healthcare software security using quantum computing methods. Although the placement of virtual machines in cloud environments posed a challenge in cloud computing, Bhatt and Singhal [7] presented a hybrid metaheuristic solution to address this issue. Krishna and Rajarajeswari [8] improved feature selection in bioinformatics datasets by merging swarm intelligence with mutual information estimates, thus enhancing the accuracy of disease identification. Aryuni et al. [9] used the SMOTE method to make predictions for minority classes more accurate, and this technique resolved the problem of uneven learning when classifying heart diseases. Furthermore, Musanase et al. [10] showcased the beneficial applications of fuzzy logic and machine learning in agriculture by forecasting soil quality for optimal potato growth in Rwanda. ATT-NestedUnet, created by Hu et al. [11], is a semantic segmentation model using deep learning to detect sugar beetroots and weed species. Chauhan and Choi [12] used a machine learning approach with stacked classifiers and mutual information to increase the accuracy of ADHD diagnoses. Debnath and Mondal [13] use CNN and PCA for dynamic variance control in audio compression. Olabanjo et al. [14] developed a model to manage complex, interrelated network traffic data, focusing on intelligent network traffic analysis and categorization. Using machine learning, Alrahhal and Supreethi [15] enhanced content-based picture retrieval.

3. Hybrid Deep-Unified Model (HDUM)

HDUM represents an innovative approach to image classification, that uses strengths of three deep learning architectures: ResNet, DenseNet, and InceptionNet. This integration aims to harness the unique capabilities of each model to increase the overall performance and optimization of classification system. Input data are pre-processed and the features are extracted. The ensemble's upgraded DenseNet structure densely connects dense blocks. The model can effectively transmit and reuse features to derive meaningful representations from input. The con-structed DenseNet that includes cascaded convolutional layers can be able to detect more complex patterns and features that will lead to an improvement in performance. The inception modules enable the model to describe the complex picture patterns capturing attributes of varying sizes. Convolutional and max pooling layers enhance feature extraction, algorithm capacity and information processing at optimum inception, and enhance performance. Components affected by ResNet enhance gradient flow and ensemble depth. In Figure 1, hybrid model must be better than

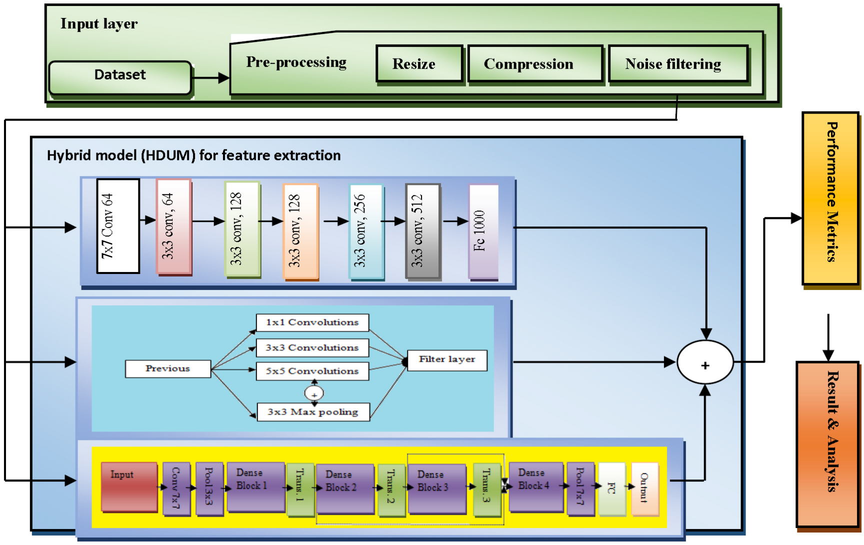

Figure 1

Framework of the HDUM

the standard model. The full structure of the proposed Hybrid Deep Unified Model (HDUM), which can effectively extract and classify features and evaluate their performance, is presented in Figure 1.

The structure consists of three significant steps; input processing, learning hybrid features, and performance analysis. The input stage takes raw datasets in the first phase which undergo pre-processing operations which include resizing, compression, and noise filtering. The steps make sure that the data are uniform, compact and contain no irrelevant distortions and thus the quality of features yielded in later stages is improved. The second phase is the HDUM feature extraction module which is a combination of optimized DenseNet, InceptionNet, and ResNet to produce both spatial and ab-abstract representations of the input data. The ResNet branch uses several convolutional layers with different filter sizes (7×7, 3×3, etc.), gradually increasing the number of feature maps (64, 128 and 512 feature maps).

4. Selection of Dataset & Preprocessing

4.1 *Selection of datasets*

This study utilizes a graphical dataset to train and test CNN-predicated models for accuracy prognostications. A total of five data sets is utilized, of which four datasets emanate from dataset repositories and the fifth dataset is a real-time dataset designed utilizing NFT mania, and their details are given in Table 1.

Table 1

Datasets Description

Dataset	Dataset Type	Size of Datasets
Brain: MRI &CT scan	Graphical	2503 brain CT scan and 2501 MRI Images.
Mental health detection	Graphical	Flickr30k Entities, which augments 158k captions by 244k co-ref. chains with 158915 images.
Kidney stone Detection	Graphical	Normal = 5077, Cyst=3709, Tumour=2283, Stone=1377
Skin cancer detection	Graphical	Total images = 200
NFT data	Graphical	Total Images = 1000

4.2 *Image Resizing and Compression*

To save space, the image's DPI is also decreased. Compression affects the final picture quality. Table 2 displays the original and compressed image sizes at 10-image intervals. With regard to both uncompressed and compressed are represented in Table 2.

Table 2

Image Compression Impact

Image	Before compression	After compression
10	15.776	8.371
20	21.815	16.092
30	40.542	28.99
40	45.848	37.054
50	55.086	49.716

5. Implementation of HDUM

HDUM is initialized for image classification via the integration of optimized DenseNet, ResNet, and InceptionNet. This model is capable of providing better accuracy during classification. The epochs, training and testing sizes, learning rates, and batch sizes are specified, followed by training and testing operations. Beginning with data preparation, the algorithm preprocesses the input data and initializes the pretrained models. Through feature extraction, features are extracted from intermediate layers of each optimized model, utilizing the unique capabilities of the ResNet, DenseNet, and Inception architectures. Second, the algorithm splits into separate paths for the optimized ResNet, DenseNet, and Inception modules, using each one's unique ability to extract features.

Table 3

Comparison of the accuracy parameters

Data Set	Performance Metric	CNN	ResNet	DenseNet	Incep-tion	Hybrid CNN and VGG16	HDUM
Brain Tumour Detection	**Recall**	95.19	96.19	96.19	95.23	96.51	98.29
	precision	95.09	96.49	96.56	95.61	96.62	98.53
	F1-score	95.49	96.19	96.12	95.89	96.23	98.62
	Accuracy	95.92	96.89	96.84	95.92	96.92	98.92
Kidney Stone Detection	**Recall**	94.39	96.29	95.21	94.43	96.43	98.32
	precision	94.99	96.19	95.13	94.13	96.78	98.43
	F1-score	94.39	96.09	95.54	94.19	96.35	98.71
	Accuracy	94.89	96.29	95.89	94.12	96.99	98.89
Skin cancer detection	**Recall**	94.09	96.39	96.39	95.32	96.72	98.04
	precision	94.19	96.79	95.64	94.21	96.23	98.51
	F1-score	95.49	96.72	96.42	95.34	96.61	98.75
	Accuracy	95.53	96.98	96.89	95.84	97.98	98.98
Mental Health Detection	**Recall**	95.69	96.99	95.34	94.41	96.42	98.22
	precision	95.39	96.39	96.41	95.53	96.13	98.31
	F1-score	94.09	96.29	95.79	95.62	96.35	98.45
	Accuracy	95.73	96.98	95.89	95.86	96.83	98.88
NFT Dataset	**Recall**	95.19	96.69	96.45	94.91	96.76	98.87
	precision	96.59	96.79	96.72	95.02	96.82	98.88
	F1-score	95.69	96.29	96.45	95.12	96.83	98.98
	Accuracy	95.79	96.98	96.78	95.88	96.89	98.99

6. Comparison of HDUM with Other Models

HDUM performance evaluation involves assessing its ability to find specific objectives. The performance evaluation choice indicators should align with the goals, and tasks of the model designed to solve. Four conventional algorithms, CNN, ResNet, DenseNet, and InceptionNet, are considered along with two hybrid algorithms, i.e. a hybrid algorithm with the integration of VGG16 & CNN and HDUM with the integration of optimized ResNet, DenseNet and InceptionNet, to train and test datasets. Deep learning models such as CNN, ResNet, DenseNet, Inception, and hybrid models such as HDUM, achieve high accuracy rates in medical image detection, enhancing patient care outcomes. Table 3 and Figure 2 compare the performance parameters with diverse datasets.

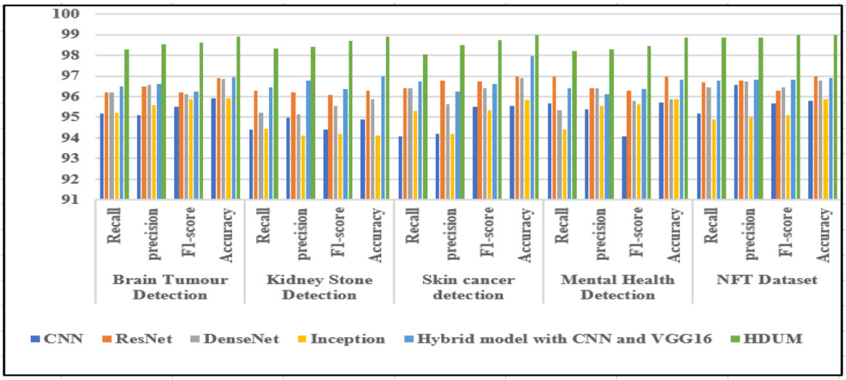

Figure 2

Comparison of the accuracy parameters

7. Conclusion

The HDUM enhances the efficiency of picture categorization. Research evaluates the HDUM image classification system using recall, precision, accuracy, and F1_score, and compare it to CNN, ResNet, DenseNet, Inception, and hybrid models with CNN and VGG16. Using four separate datasets for mental health analysis, skin cancer diagnosis, kidney stone detection, and brain tumor detection, the HDUM attained performance metrics of approximately 98% for F1_score and 99% for other performance metrics. Many diverse fields such as autonomous vehicles, agriculture, retail, and security, which drive enhanced efficiency and decision-making and adapt to evolving technological landscapes, also expect the HDUM to perform better.

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