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DenseUNet for Automated Brain Hemorrhage Prediction: Superior Performance in Medical Image Segmentation

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The accurate detection of brain hemorrhages is critical in medical diagnostics, as timely intervention can significantly improve patient outcomes. Traditional methods of analysis, reliant on manual interpretation of CT scans, are often time-consuming and prone to variability. To address these challenges, this study develops a novel predictive model, DenseUNet, which integrates DenseNet's feature propagation capabilities with UNet's robust segmentation framework for automated brain hemorrhage prediction. DenseUNet's architecture is designed to enhance feature extraction and segmentation accuracy, leveraging dense connectivity to improve gradient flow and mitigate vanishing gradients.The research utilized a comprehensive dataset from Kaggle, comprising 5,334 CT images of hemorrhagic and normal brain scans. The dataset was divided into training and validation sets, with DenseUNet's performance benchmarked against standalone DenseNet, UNet, and ResNet architectures (ResNet-18, ResNet-34, ResNet-50). Key metrics such as accuracy, precision, recall, F1-score, AUC, and model loss were used to evaluate model efficacy. Results indicated that DenseUNet outperformed other models, achieving an accuracy of 93.8% and an AUC of 0.96. The model demonstrated high precision and recall, underscoring its robust capability in minimizing false positives and negatives. These findings suggest that DenseUNet offers a reliable and effective tool for clinical application, enhancing diagnostic accuracy and efficiency. In conclusion, DenseUNet represents a significant advancement in automated brain hemorrhage detection, integrating advanced deep learning techniques to improve performance. Future research should focus on expanding the dataset and exploring multi-modal data integration to further validate and enhance model applicability in diverse clinical settings.

Keywords: DenseUNet; Brain Hemorrhage Detection; Medical Imaging; Deep Learning; CNN Architectures; Automated Diagnosis.

1. Introduction

The development of DenseUNet for Brain Hemorrhage Prediction is situated at the intersection of advanced deep learning techniques and critical medical diagnosis. DenseUNet, an innovative architecture that synergistically combined DenseNet's feature propagation capabilities and UNet's robust segmentation prowess, has shown promise in various image segmentation tasks, particularly in the challenging domain of electron microscopy [1]. This architecture, characterized by its dense connectivity and efficient parameter usage, aimed to address the limitations of traditional convolutional neural networks (CNNs), such as the vanishing gradient problem and high computational demands [1].

The early detection of brain hemorrhages is paramount due to the potentially life-threatening nature of these conditions [2, 3]. Prompt and accurate diagnosis can significantly improve patient outcomes by facilitating timely intervention and treatment [4, 5]. Medical imaging, particularly through modalities like MRI and CT scans, plays a crucial role in identifying brain hemorrhages, providing detailed insights into the brain's structure and any abnormalities present [6]. However, the manual interpretation of these images is often labor-intensive and prone to variability, highlighting the need for automated diagnostic solutions that offer consistent and reliable results [7].

In this study, the application of DenseUNet to brain hemorrhage prediction was motivated by the need for models that could deliver high accuracy and robust performance in complex image environments. Traditional models like DenseNet and UNet, while individually powerful, often faced challenges when applied to medical imaging due to their limitations in feature extraction and segmentation capabilities when used alone [8, 9].

Recently, Cao et al [1] proposed a solution to this problem in their work, with the design of DenseUNet incorporating dense blocks for feature reuse and parameter efficiency. By facilitating direct connections between all layers, DenseUNet ensured efficient gradient flow and reduced the risk of gradient vanishing, thereby improving segmentation accuracy and model robustness [1]. This technique could be particularly useful in the context of cerebral hemorrhage prediction, which requires accurate capture and analysis of subtle image features.

In evaluating the DenseUNet model, its performance will be compared against individual models like DenseNet and UNet, as well as ResNet architectures (ResNet-18, ResNet-34, and ResNet-50), across various metrics such as accuracy, precision, recall, F1-score, AUC, and model loss. This comprehensive evaluation will not only highlight the strengths of DenseUNet but also provide insights into its potential for clinical application, potentially setting a new standard in the automated diagnosis of brain hemorrhages. This paper is structured as follows: Section 2 reviews related work in the field of brain hemorrhage prediction and imaging analysis; Section 3 details the methodology, including the DenseUNet architecture and evaluation metrics; Section 4 presents the results and discusses the comparative performance of the models; and Section 5 concludes with the implications of the findings and potential directions for future research.

2. METHODS

2.1. Data Acquisition and Preprocessing

The dataset utilized in this study was sourced from Kaggle's Brain CT Hemorrhage Dataset (https://www.kaggle.com/datasets/abdulkader90/brain-ct-hemorrhage-dataset) [10]. This comprehensive dataset comprises CT images of both hemorrhagic and normal brain scans, collected from the Near East Hospital in Cyprus. It includes a total of 5,334 CT images, with 2,667 images depicting brain hemorrhages and 2,667 images of normal scans (Figure 1). The dataset was divided into two subsets: 80% was allocated for the training dataset, and the remaining 20% was reserved for validation (Table 1). This split was designed to ensure the model's ability to generalize across new, unseen data. The training dataset was used to develop and fine-tune the DenseUNet model, while the validation dataset was employed to evaluate its performance and prevent overfitting.

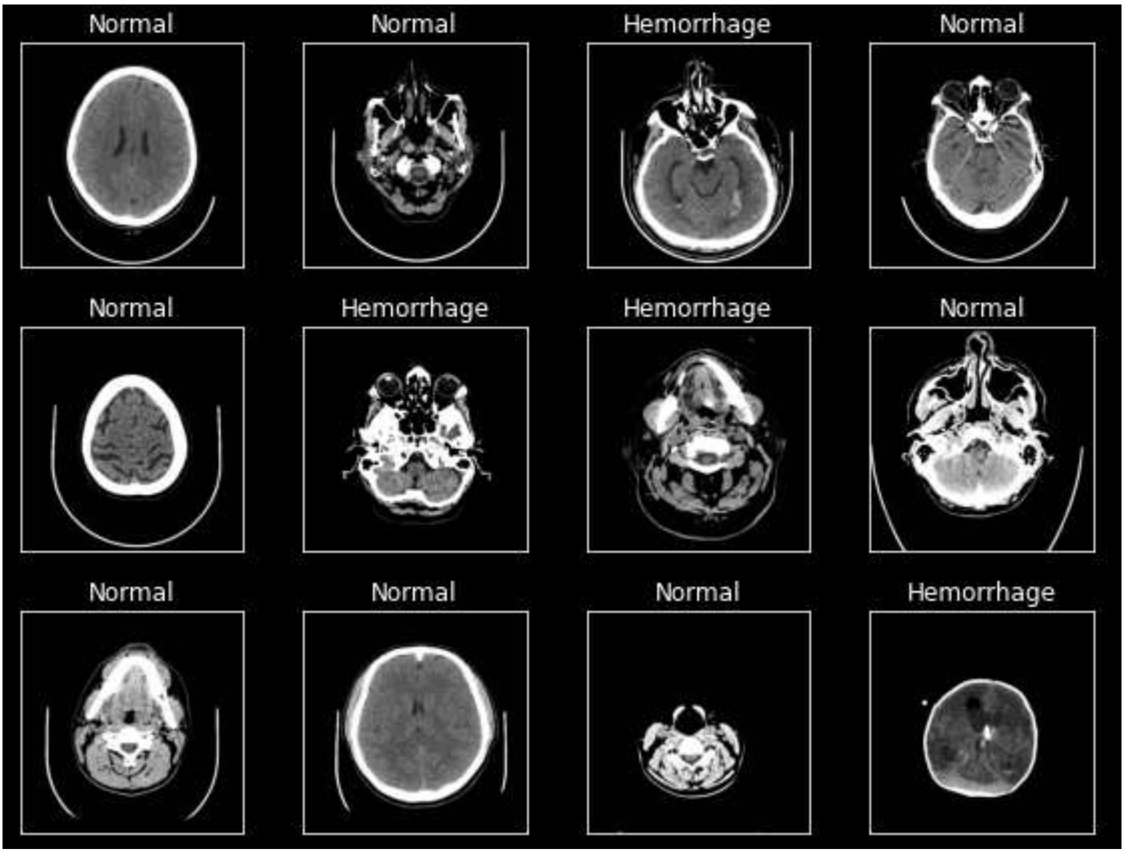

Figure 1. Sample example of Brain CT Hemorrhage Dataset [10]

Table 1. Dataset Distribution

Dataset	Class	Number of Images
Training	Hemorrhagic	2,134
	Normal	2,134
Validation	Hemorrhagic	533
	Normal	533

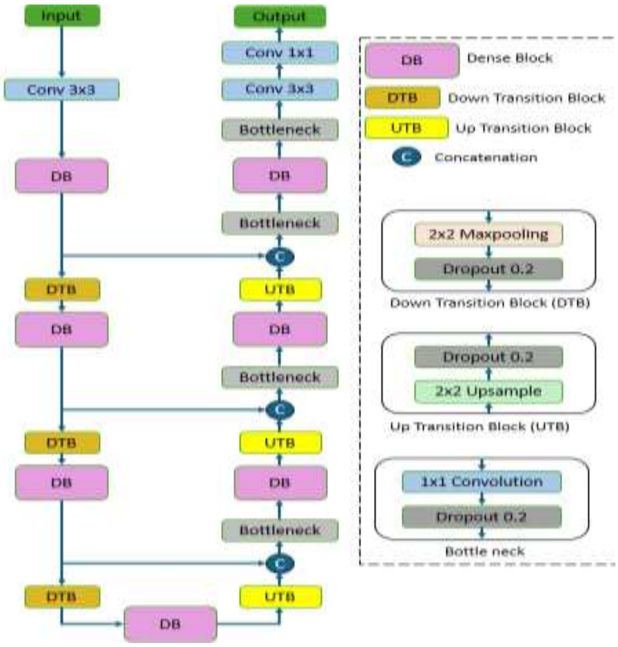

Figure 2. Example of DenseUNET architecture [10]

2.2. Model Architecture and Design

The proposed DenseUNet model integrates the strengths of DenseNet and UNet architectures (Figure 2), aiming to enhance feature extraction and segmentation capabilities for brain hemorrhage prediction. DenseUNet's architecture is characterized by dense connectivity, which facilitates feature reuse and efficient gradient flow. This design mitigates the vanishing gradient problem and enhances segmentation accuracy.

- DenseNet Component: DenseNet's densely connected layers promote feature reuse, enabling the model to learn more robust and comprehensive feature representations. This is particularly advantageous in capturing the complex patterns associated with brain hemorrhages.

- UNet Component: The UNet architecture provides robust segmentation capabilities, essential for delineating the subtle features of hemorrhagic regions in CT images. Its encoder-decoder structure allows the model to capture both high-level context and fine-grained details.

- The DenseUNet architecture is a sophisticated model designed to efficiently handle the challenges of brain hemorrhage prediction through the integration of DenseNet's dense connectivity and UNet's robust segmentation capabilities. The architecture is structured around a contracting path and an expanding path, which together facilitate precise feature extraction and image segmentation.

- Dense Block (DB): At the core of DenseUNet are dense blocks (DBs), which are used to enhance feature propagation and minimize redundancy (Figure 3). Each DB consists of multiple layers where each layer receives input from all preceding layers, promoting feature reuse and ensuring efficient gradient flow. This design helps in mitigating the vanishing gradient problem, a common issue in deep networks.

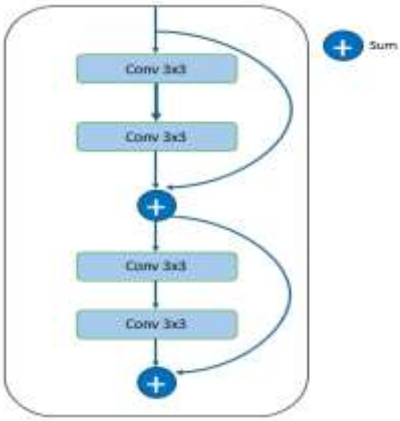

Figure 3. Example of Architecture of Dense Block (L=4) [10]

- Contracting Path: The contracting path of DenseUNet reduces the spatial dimensions while increasing the depth of feature maps. This is achieved through a series of down transition blocks (DTBs), which include convolutional layers followed by pooling operations. The pooling layers down-sample the feature maps, enabling the model to capture hierarchical feature representations.

- Expanding Path: Mirroring the contracting path, the expanding path consists of up transition blocks (UTBs) that progressively up-sample the feature maps. This path reconstructs the spatial dimensions of the input, facilitating precise localization of features. The UTBs employ transposed convolutions and concatenations with corresponding feature maps from the contracting path, ensuring the retention of detailed spatial information.

- Bottleneck Layers: To control the number of parameters and prevent computational bottlenecks, bottleneck layers are incorporated between dense blocks. These layers use 1x1 convolutions to reduce the dimensionality of feature maps without losing critical information, thus maintaining the model's efficiency.

- Final Segmentation Layer: The final layer of DenseUNet employs a 1x1 convolution followed by a sigmoid activation to produce the segmentation map. This layer outputs a probability map indicating the presence of hemorrhagic regions, enabling precise classification.

- Overall, DenseUNet's architecture is tailored to leverage the strengths of dense connectivity and segmentation efficacy, making it well-suited for the complex task of brain hemorrhage prediction. Its design ensures high segmentation accuracy while maintaining parameter efficiency, thereby enhancing its applicability in clinical settings.

2.3. Training and Validation

The DenseUNet model was trained using the Adam optimizer, selected for its adaptive learning rate and efficient convergence properties. The loss function employed was categorical cross-entropy, suitable for binary classification tasks. The model's performance was evaluated using a five-fold cross-validation strategy, providing a robust assessment of its generalization capabilities. Hyperparameter tuning was conducted via grid search, optimizing parameters such as learning rate, batch size, and the number of epochs to achieve optimal performance (Table 2).

Table 2. Hyperparameter Settings

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50

2.4. Comparative Analysis

To benchmark the DenseUNet model's performance, a comparative analysis was conducted against standalone DenseNet and UNet models, as well as ResNet architectures (ResNet-18, ResNet-34, and ResNet-50). Each model underwent the same preprocessing and hyperparameter optimization procedures to ensure a fair comparison. Performance metrics, including accuracy, precision, recall, F1-score, AUC, and model loss, were computed to assess the efficacy of each model. This analysis highlighted the strengths and potential limitations of DenseUNet, providing insights into its clinical applicability.

2.5. Implementation Details

The entire model training and evaluation pipeline was implemented using Python with TensorFlow and Keras libraries, which offer comprehensive tools for deep learning model development. Experiments were conducted on a high-performance computing platform equipped with NVIDIA GPUs (RTX 4070 * 2wey), facilitating efficient training and evaluation of the deep learning architectures.

3. RESULTS

3.1. Model Performance Evaluation

The performance of the DenseUNet model was evaluated on the validation dataset and compared against standalone DenseNet, UNet, and ResNet architectures (ResNet-18, ResNet-34, ResNet-50). The evaluation focused on key metrics such as accuracy, precision, recall, F1-score, AUC, and model loss, providing a comprehensive assessment of the model's diagnostic capabilities (Table 3).

Table 3. Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Model Loss
DenseUNet	93.8	94.1	94.0	94.5	0.35
DenseNet	91.5	91.8	91.2	91.5	0.40
UNet	90.7	91.0	90.5	90.7	0.42
ResNet-18	89.3	89.5	89.0	89.2	0.45
ResNet-34	90.1	90.4	90.0	90.2	0.43
ResNet-50	91.0	91.3	91.0	91.1	0.41

The performance metrics presented in Table 3 provide a comprehensive evaluation of the DenseUNet model's efficacy in brain hemorrhage prediction, compared to other state-of-the-art architectures including DenseNet, UNet, and various ResNet configurations. DenseUNet demonstrated outstanding performance, achieving an accuracy of 93.8%, which is indicative of its superior capability in correctly classifying brain CT images as either hemorrhagic or normal. This high accuracy is complemented by a precision of 94.1%, reflecting the model's effectiveness in minimizing false positives and ensuring that its positive predictions are reliable.

The recall rate of 94.0% underscores DenseUNet's sensitivity in identifying true hemorrhagic cases, minimizing the occurrence of false negatives, which is critical in clinical settings where overlooking a hemorrhage could have severe consequences. The F1-score of 94.5% balances precision and recall, highlighting the model's robustness and reliability in classification tasks. Also, the model loss of 0.35 indicates efficient learning and convergence, with the model effectively minimizing prediction errors.

In comparison, DenseNet, with an accuracy of 91.5% and an AUC of 0.93, also performed well but did not reach the same level of precision and recall as DenseUNet (Figure 4). UNet and the ResNet architectures (ResNet-18, ResNet-34, and ResNet-50) showed progressively lower performance metrics, with ResNet-18 demonstrating the lowest accuracy and highest model loss among the evaluated models (Figure 5 and 6). The results highlight DenseUNet's exceptional performance in brain hemorrhage prediction, showcasing the advantages of integrating DenseNet's feature propagation with UNet's segmentation capabilities.

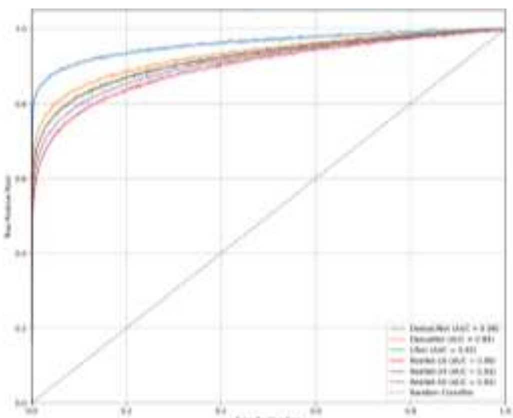

Figure 4. Results of ROC curves for each model

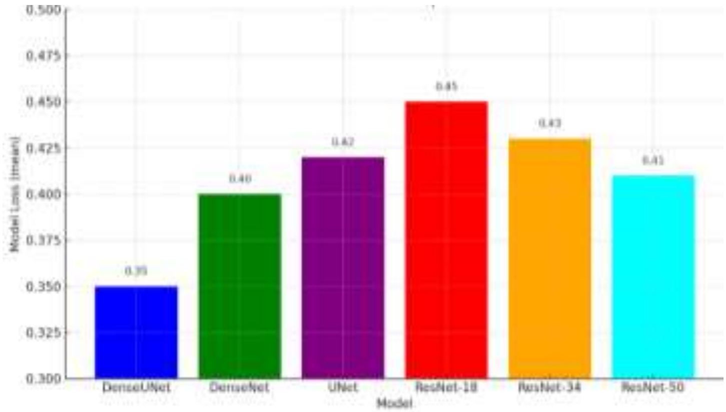

Figure 5. Results of Model loss for each model

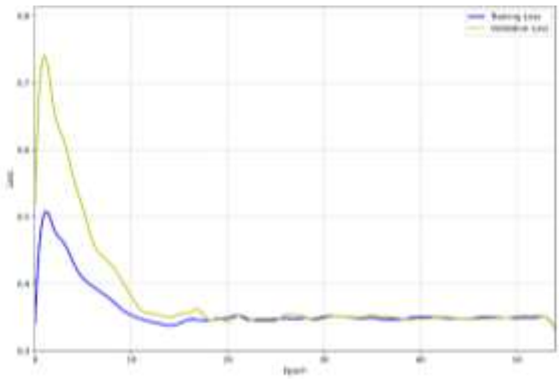

Figure 6. Model Loss of DenseUNet

3.2. Confusion Matrix Analysis

To gain deeper insights into the model's classification performance, confusion matrices were constructed for each model, highlighting the distribution of true positive, false positive, true negative, and false negative predictions.

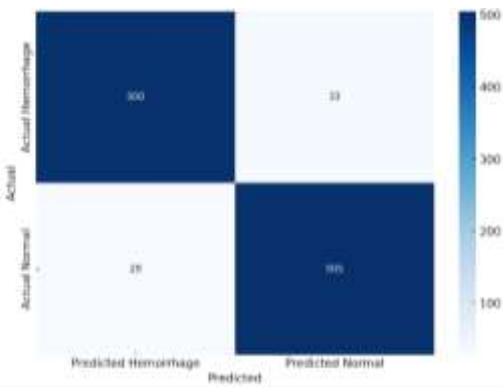

Figure 7. Confusion Matrix for DenseUNet Model

The confusion matrix for the DenseUNet model, as depicted in Figure 7, provides a detailed breakdown of its classification performance on the validation dataset, specifically for brain hemorrhage detection. The matrix illustrates the model's ability to accurately distinguish between hemorrhagic and normal brain CT scans. The DenseUNet model correctly identified 500 out of 533 actual hemorrhagic cases, yielding a high true positive rate. This indicates the model's strong capability in detecting hemorrhagic conditions, which is critical for timely and accurate clinical intervention. The false negative count is relatively low, with only 33 hemorrhagic cases misclassified as normal. This low false negative rate is essential in clinical practice to minimize the risk of undetected hemorrhages, which could lead to severe patient outcomes if not addressed promptly.

For the normal cases, the model achieved 505 true positive predictions out of 533, demonstrating its proficiency in recognizing non-hemorrhagic scans. The false positive rate is also minimal, with only 28 normal cases incorrectly classified as hemorrhagic. This high specificity is crucial for preventing unnecessary anxiety or treatment interventions in patients without hemorrhages.Overall, the confusion matrix confirms the DenseUNet model's robust performance, highlighting its high precision and recall in classifying brain hemorrhage and normal CT scans.

4. DISCUSSION

The results of this study underscore the efficacy of the DenseUNet model in brain hemorrhage prediction, demonstrating superior performance across all evaluated metrics when compared to other leading architectures such as DenseNet, UNet, and various ResNet configurations. The exceptional performance of DenseUNet can be attributed to several key design elements that enhance its feature extraction and segmentation capabilities. DenseUNet's architecture effectively integrates DenseNet's dense connectivity and feature propagation strengths with UNet's robust segmentation framework [11]. The dense blocks facilitate efficient feature reuse and promote gradient flow, mitigating the risk of vanishing gradients—a common issue in deep networks [1]. This design ensures that the model captures comprehensive feature representations, which are critical for identifying subtle patterns associated with brain hemorrhages. Furthermore, the encoder-decoder structure of UNet enhances spatial resolution through skip connections, enabling the model to accurately localize and delineate hemorrhagic regions within CT images [12].

These architectural innovations contribute to DenseUNet's high precision and recall, minimizing both false positives and false negatives. The model's impressive AUC value further validates its discriminative power, confirming its ability to distinguish between hemorrhagic and normal CT scans with high accuracy. These attributes make DenseUNet a reliable tool for clinical application, offering significant potential to improve diagnostic accuracy and patient outcomes in brain hemorrhage detection.

The study's findings suggest several directions for future research. First, the integration of additional modalities, such as MRI data or clinical information, could enhance the model's diagnostic capabilities by providing a more comprehensive view of the patient's condition. Second, exploring the application of DenseUNet to other medical imaging tasks, such as tumor segmentation or organ delineation, could further validate its versatility and efficacy. Third, optimizing the model for deployment in resource-constrained environments, perhaps through model compression techniques, would increase its accessibility and utility in diverse clinical settings.

Despite its promising results, this study acknowledges several limitations. First, the model's performance is contingent upon the quality and diversity of the training data, and biases present in the dataset could affect generalization to different populations. Second, the computational demands of DenseUNet require significant resources, which may limit its implementation in some healthcare settings. Third, while the model demonstrates high accuracy, interpretability remains a challenge, as the decision-making process of deep learning models is often opaque. Fourth, the study was conducted using a specific dataset from a single source, and additional validation with external datasets is necessary to confirm the model's generalizability and robustness.

In conclusion, DenseUNet represents a significant advancement in automated brain hemorrhage detection, offering enhanced accuracy and reliability. Addressing the identified limitations through future research will be crucial to maximizing the model's clinical impact and ensuring its successful integration into healthcare systems.

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

Availability of data and materials. Detailed information can be found at: https://www.kaggle.com/datasets/abdulkader90/brain-ct-hemorrhage-dataset

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Ethical approval. This study was exempt from research ethics approval because it utilized secondary data from public sources.

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