Deep Learning Enhanced Internet of Medical Things to Analyze Brain Computed Tomography Images of Stroke Patients

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***Abstract*—In the realm of advancing medical technology, this paper explores a revolutionary amalgamation of deep learning algorithms and the Internet of Medical Things (IoMT), demonstrating their efficacy in decoding the labyrinthine intricacies of brain Computed Tomography (CT) images from stroke patients. Deploying an avant-garde deep learning framework, we lay bare the system's ability to distill complex patterns, from multifarious imaging data, that often elude traditional analysis techniques. Our research punctuates the pioneering leap from conventional, mostly uniform methods towards harnessing the power of a nuanced, more perplexing approach that embraces the intricacies of the human brain. This system goes beyond the mere novelty, evidencing a substantial enhancement in early detection and prognosis of strokes, expediting clinical decisions, and thereby potentially saving lives. Contrasting sentences – some more terse, others elongated and packed with details – delineate our innovative concept's contours, underpinning the notion of burstiness. Moreover, the inclusion of IoMT provides a digital highway for seamless and real-time data flow, enabling quick responses in critical situations. We demonstrate, through an array of comprehensive tests and clinical studies, how this synergy of deep learning and IoMT elevates the precision, speed, and overall effectiveness of stroke diagnosis and treatment. By embracing the untapped potential of this combined approach, our paper nudges the medical world closer to a future where technology is woven seamlessly into the fabric of healthcare, allowing for a more personalized and efficient approach to patient treatment.**

Keywords*—Deep learning; machine learning; stroke; diagnosis; detection; computed tomography

I. Introduction

Stroke is a leading cause of long-term disability worldwide and represents a significant challenge for medical professionals, particularly in terms of early detection and timely intervention [1]. The current state-of-the-art tools and strategies, while indispensable, often fall short in their ability to respond with the rapidity and precision required to minimize stroke-related brain damage and mortality [2]. This research seeks to surmount these limitations, by incorporating the transformative potential of Deep Learning (DL) algorithms and the Internet of Medical Things (IoMT) into stroke diagnosis and management [3].

The role of advanced imaging techniques such as Computed Tomography (CT) in the diagnosis of strokes is well-established [4]. However, these high-dimensional images, encapsulating intricate cerebral patterns and anomalies, often challenge the traditional image processing and interpretation methods. Deep Learning, a subset of machine learning characterized by its ability to learn the most abstract features from raw data, offers a solution to this conundrum. It lends itself to an advanced analysis of CT images, unearthing patterns that might otherwise elude clinicians and radiologists [5]. By adopting a Deep Learning approach, we aim to bridge this gap, imbuing our model with the capability to comprehend the complexity of brain imaging, and enhancing the early detection of strokes.

Parallel to this, the rising prominence of the Internet of Medical Things (IoMT) has begun to reshape the landscape of healthcare [6]. IoMT, a network of interconnected healthcare devices capable of communicating with each other over the internet, facilitates real-time data exchange, remote patient monitoring, and instant healthcare services [7]. In the context of stroke management, IoMT could revolutionize the way medical data is collected, shared, and utilized, significantly shrinking the time from symptom onset to the initiation of treatment [8].

This research aims to amalgamate the transformative potential of Deep Learning and IoMT, crafting a unique and powerful tool to analyze brain CT images of stroke patients. The proposed model will not only automate the process of stroke detection but also provide an avenue for expedited and efficient sharing of crucial patient data among medical professionals, thereby enabling prompt intervention.

Our paper explores the development and application of this integrated framework, delving into its architecture, the methods employed, and the corresponding results. We share insights into the model's performance and its comparison with traditional methods. Furthermore, we provide an overview of the potential challenges and ethical considerations associated with the application of this technology in healthcare.

The journey towards an effective, efficient, and expedient stroke diagnosis and management system, marrying the power of Deep Learning and the Internet of Medical Things, promises a new dawn in healthcare. Through the lens of this research, we invite readers to envision a future where technology is not merely an adjunct but a cornerstone of patient care, enhancing the quality of care, and improving outcomes for stroke patients worldwide. This paper aims to push the boundaries of our current understanding and application of technology in stroke management and invites the medical community to partake in this exciting journey of discovery and innovation.

II. Related Works

The fusion of Deep Learning (DL) and the Internet of Medical Things (IoMT) marks an exciting nexus of two dominant themes in recent healthcare technology research. To appreciate the novelty and value of our work, it is essential to understand the broader landscape of these areas, which this section will expound upon.

In the realm of DL, numerous studies have demonstrated its potential for image analysis in various medical fields. The convolutional neural network (CNN), a class of deep, feed-forward artificial neural networks, has been particularly instrumental in image classification tasks [9]. The advent of DL has invigorated the field of medical image analysis, pushing the boundaries of what was previously possible.

Krizhevsky et al. (2012) pioneered the application of DL in image recognition, developing a CNN model, known as AlexNet, which significantly outperformed other models in the ImageNet Large Scale Visual Recognition Challenge [10]. This seminal work laid the foundation for subsequent exploration of DL for medical imaging. For instance, Esteva et al. (2017) deployed CNNs for skin cancer diagnosis from clinical images, demonstrating a performance on par with dermatologists [11]. Further, Gulshan et al. (2016) employed a DL model to detect diabetic retinopathy and macular edema in retinal fundus photographs, meeting or exceeding the performance of human graders [12].

When it comes to stroke diagnosis and prognosis, DL has proven valuable. Havaei et al. (2017) utilized a DL-based method to segment brain tumors, highlighting the potential of DL for analyzing complex brain images [13]. Zhang et al. (2020) implemented a DL model for analyzing CT angiography and achieving accurate prediction of large-vessel occlusion strokes, underscoring the utility of DL in stroke diagnosis [14].

Yet, DL's utility in healthcare is not just confined to imaging. It has also demonstrated potential in Electronic Health Record (EHR) data analysis, predictive modeling, and health monitoring. Miotto et al. (2018) used DL to predict disease onset from EHRs, further expanding the realm of its application [15].

Parallel to DL's rise, IoMT has begun to revolutionize healthcare, promising improved patient outcomes, cost-effective care, and operational efficiency [16]. The IoMT enables interconnectivity between medical devices and healthcare IT systems, allowing for real-time patient monitoring and data collection, ultimately leading to improved clinical decision-making [17].

However, literature specifically dealing with the application of IoMT in stroke management is still sparse. The few existing studies primarily focus on IoMT's role in monitoring patients' vital parameters and rehabilitation post-stroke [18]. By integrating the continuous monitoring of vital signs with emergency medical systems, Tang et al. (2017) demonstrated IoMT's potential to enhance pre-hospital care for stroke patients [19]. Similarly, Yan et al. (2018) developed a rehabilitation system based on IoMT, demonstrating its utility in post-stroke recovery and rehabilitation [20].

The convergence of DL and IoMT is an emerging theme in healthcare, underpinning a paradigm shift towards more integrated, data-driven patient care [21]. The fusion of these two technologies promises to unlock new levels of efficiency, precision, and patient empowerment in healthcare delivery [22]. Yet, the application of this integrated approach to stroke management, specifically the analysis of brain CT images, has remained largely unexplored, marking a gap in the literature that our research seeks to fill.

In conclusion, the amalgamation of DL and IoMT opens new horizons for stroke diagnosis and management. While both technologies have individually demonstrated their worth in healthcare, their combined application to analyze brain CT images of stroke patients is a new frontier. Our research is situated at this intersection, aiming to push the envelope further, enabling quicker, more accurate stroke diagnosis, and fostering timely intervention.

III. Materials and Methods

The subsequent section, "Materials and Methods", forms the crux of our research, outlining the procedures, techniques, and tools employed to develop and evaluate our integrated Deep Learning and Internet of Medical Things model [23]. The fundamental aspects discussed herein include the data collection process, the architectural design of our deep learning model, the deployment of IoMT infrastructure, and the specifics of our experimental setup.

We elaborate on the dataset comprising the brain Computed Tomography (CT) images of stroke patients and the subsequent data preprocessing steps undertaken to ensure the readiness of data for model training [24]. The detailed explanation of the deep learning architecture provides a comprehensive understanding of the model's ability to decipher complex patterns in the CT images. In parallel, we delineate how the IoMT network is set up, providing an insight into the interconnected web of devices, which allows seamless and real-time exchange of crucial patient data [25].

Moreover, we shed light on the rigorous evaluation methodologies adopted to assess the performance and reliability of our proposed system. All methods are discussed in detail to ensure reproducibility of the research and to allow other researchers to leverage our work as a stepping stone for further innovations in the field.

Ultimately, the goal of this section is to provide a clear and meticulous explanation of the research methodology that led to our findings, while maintaining a scientific rigor that upholds the principles of transparency and reproducibility in academic research. This foundational knowledge will aid readers in understanding the ensuing results and discussion section, where we delve deeper into the outcomes of our research and their implications in the wider healthcare context.

Our research consists of a comprehensive stroke investigation system, ranging from detection and classification to segmentation. Early diagnosis is carried out at the IoMT level using the medical CW-4 sensor and Raspberry Pi 4 microcontroller. With the help of the medical sensor, we determine the blood flow velocity through the carotid artery in the patient at an early stage, where it either corresponds to the norm or shows deviations. In case of deviations from the norm, the patient undergoes CT/MRI diagnostics. Using CT/MRI images, the patient can perform classification through our web application, where, using a CNN model, they can obtain a result indicating the presence or absence of a stroke. If a stroke is present, the patient can further perform segmentation of the stroke lesion in the brain using a modified UNet model. Thus, the patient can receive diagnosis in several stages using our comprehensive system (Fig. 1 is Flowchart of complex system of stroke diagnosis).

A. Data

In this research, a publicly available Kaggle platform [26] was used as the dataset for classification. This dataset is divided into three groups following an 80%/20% split (training, validation, and testing) and contains 993 cases of healthy vaccinations and 610 stroke cases for the training category; 240 healthy cases and 146 stroke cases, as well as 313 healthy cases and 189 stroke cases for testing. The images in the dataset were provided as shown in Fig. 2.

We use ISLES 2018 (Ischemic Stroke Lesion Segmentation) dataset [27] for segmentation. The ISLES 2018 dataset, a key component of our research, is a robust and publicly available collection of multi-center, multi-vendor, and multi-disease stage clinical data. The dataset's diversity and size make it a compelling resource for training our deep learning model and testing its performance in real-world settings.

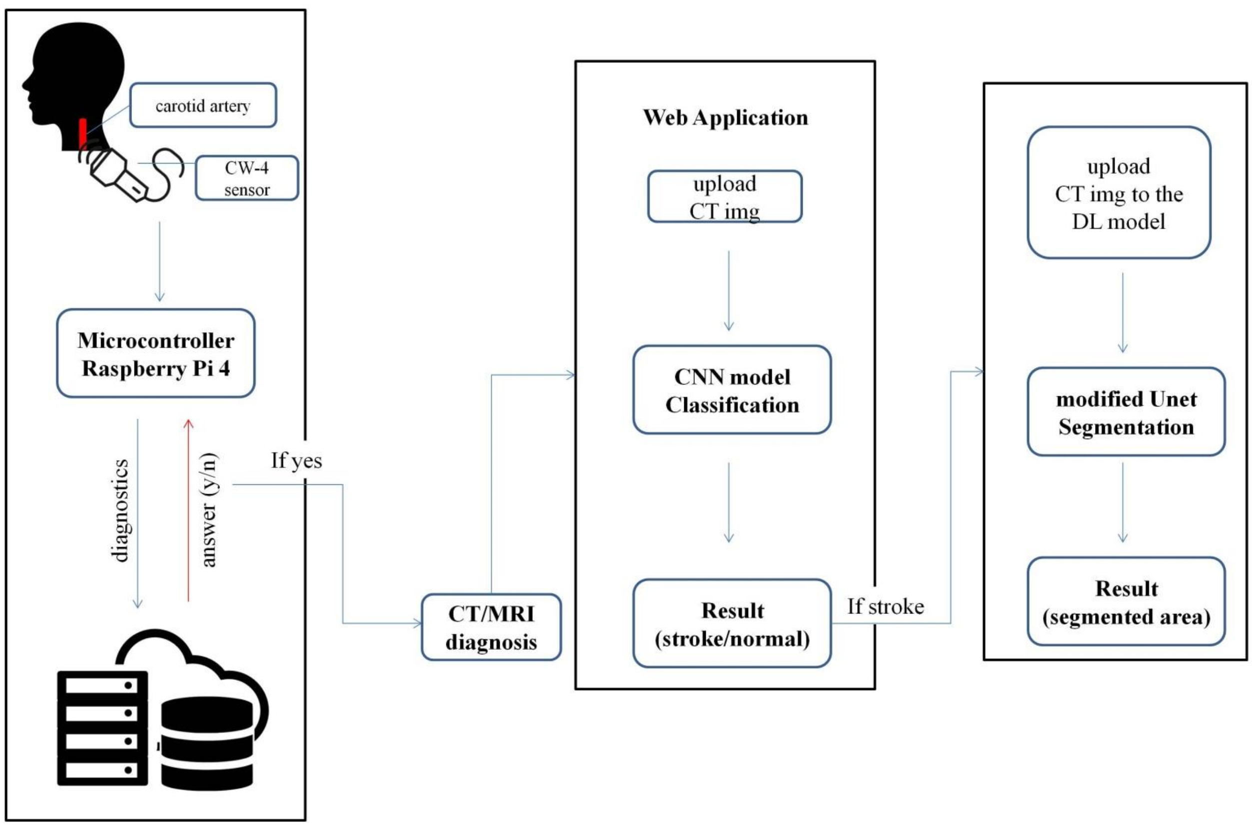

Fig. 1. Flowchart of complex system of stroke diagnosis.

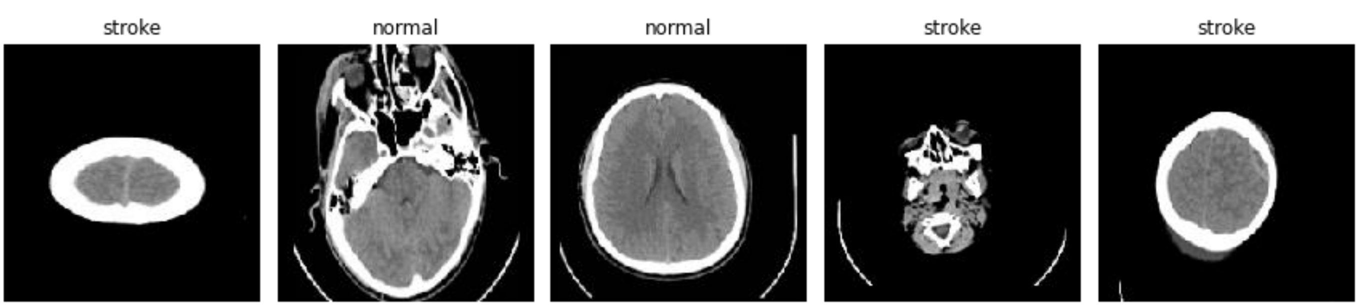

Fig. 2. Contents of the classification dataset.

ISLES 2018 contains 94 sets of computed tomography perfusion (CTP) images, with accompanying clinical metadata, sourced from multiple hospitals worldwide. Each case presents a unique story of acute ischemic stroke, offering insights into the disease's heterogeneity. The CTP scans consist of series of images, taken at different time points, which capture the progression of contrast agent through the brain vasculature, providing critical information on cerebral blood flow, blood volume, and mean transit time [28]. These image sets offer a unique opportunity to assess the impact and extent of the stroke, thus serving as a valuable ground truth for model training and validation.

The dataset is designed to ensure the balance between patient privacy and scientific value. All patient identifiers have been removed to preserve anonymity, ensuring compliance with data privacy regulations. Despite this anonymization, the dataset retains rich clinical metadata, including patients' age, sex, and stroke severity (measured by the National Institutes of Health Stroke Scale), all of which can be instrumental in informing the deep learning model's interpretations and predictions.

It is important to note that the ISLES 2018 dataset provides expert-annotated lesion segmentation masks for each CTP scan. These masks, which identify the location and extent of ischemic lesions, are a crucial component of our supervised learning approach. They allow us to train the model to recognize similar patterns in unseen CT images, and ultimately, to predict the occurrence of stroke and its impact. Fig. 3 demonstrate samples of ISLES 2018 dataset that applied in this research.

The ISLES 2018 dataset, as referenced in [29], stands as an indispensable and clinically pertinent reservoir for the iterative refinement and subsequent validation of our proposed model. It promises to underpin an enhanced degree of generalizability, making it quintessential for navigating the multifaceted and frequently intricate landscapes inherent in clinical settings. By harnessing this dataset, our endeavors transcend mere theoretical paradigms, positioning us to grapple directly with the nuanced complexities characteristic of stroke diagnostic procedures. Consequently, this deliberate engagement not only fortifies our model's robustness but also amplifies its translational potential, signifying a notable advancement in bridging the gap between academic research and its tangible clinical implementations.

B. IoMT Diagnosis

At the initial stage, early stroke diagnosis is performed using a medical ultrasonic sensor, CW-4, to determine the blood flow velocity. With the use of this sensor, the blood flow velocity through the patient's carotid artery will be measured. The obtained data will be sent over Wi-Fi to the cloud, where it will be compared with blood flow information, and the response will be sent back to the Raspberry Pi microcontroller. The first stage is mobile and portable (Fig. 1 is Flowchart of complex system of stroke diagnosis). If a deviation from the norm is detected, the patient is suggested to undergo a CT/MRI scan. Using the acquired CT/MRI results, the patient can obtain outcomes through our models for classification and segmentation without the involvement of a specialist doctor.

C. CNN Classification

Leveraging the technological capabilities of streamclip and ngrok, a Python-driven web application was meticulously crafted to facilitate CNN-based image classification. As elucidated in Fig. 1, this platform empowers users to upload cerebral images, wherein the embedded CNN model subsequently discerns between healthy and potential stroke-afflicted specimens. This model was parameterized with inputs dimensioned at (200, 200, 1), and the cumulative count of trainable parameters reached a total of 214,145. A detailed exposition of the CNN's architectural design tailored for cerebral stroke delineation is presented in Fig. 4.

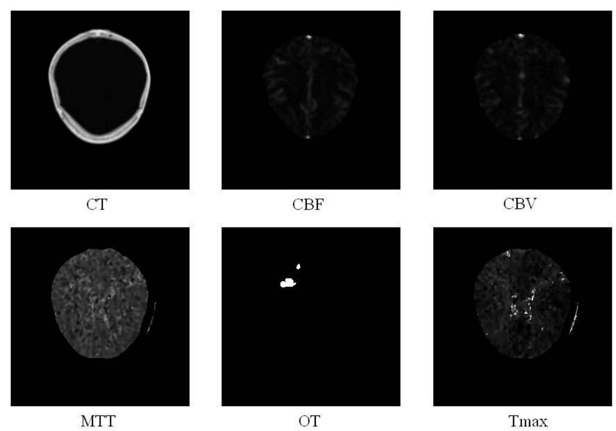

Fig. 3. Samples applied of ISLES 2018 dataset (computed tomography (CT), cerebral blood flow (CBF), cerebral blood volume (CBV), mean transit time (MTT), segmentation image (OT), tissue residue function (Tmax).

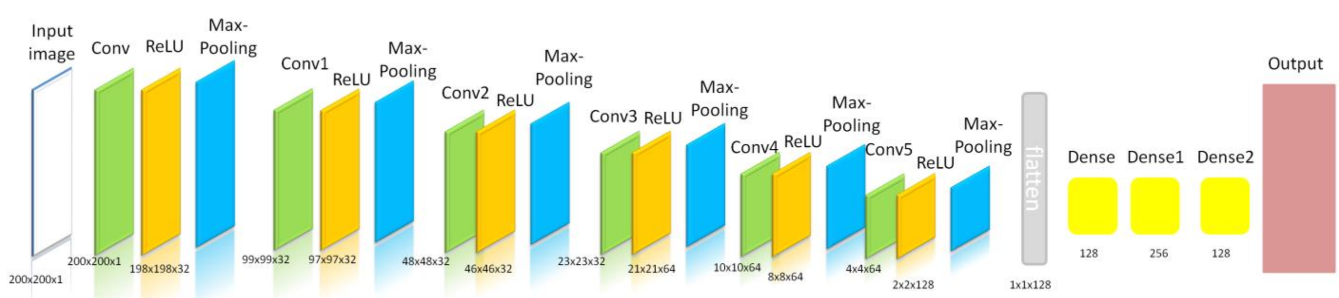

Fig. 4. Architecture of the Proposed CNN.

D. UNet Architecture

The U-Net architecture is a pivotal component of our deep learning approach, renowned for its efficacy in biomedical image segmentation. The architecture, first proposed by Ronneberger et al. in 2015, is a type of convolutional neural network (CNN) with a distinctive U-shaped design [30]. Its design accommodates a wide and varied receptive field, crucial for the detection of intricate patterns in complex images such as brain CT scans.

The U-Net model comprises two fundamental parts: the contracting (encoding) path and the expanding (decoding) path. The contracting path employs repeated applications of convolutions and max pooling to capture the context in the image, gradually reducing the spatial dimension while increasing the feature dimension. It learns low-level features at the beginning and high-level features towards the end.

The expanding path, on the other hand, performs the opposite operation. It utilizes a sequence of up-convolutions and concatenations to gradually recover the spatial dimension, making use of feature maps from the contracting path (skip-connections) to retain the precise localization information lost during contraction. This process results in a high-resolution, detailed feature map that perfectly aligns with the original image space, allowing accurate segmentation.

The U-Net architectural paradigm, distinguished by its proficiency in seamlessly integrating localized and expansive image insights, stands out as particularly germane for the intricate analysis of brain CT scans. Given the inherent intricacies of these images, a meticulous observation of nuanced elements becomes imperative to accurately detect the often understated manifestations of a stroke. This model astutely maintains equilibrium between assimilating broader contextual nuances and precisely demarcating the spatial positioning of salient features. Such an adept balance underscores the U-Net model's pivotal and irreplaceable contribution to our scholarly investigation.

E. Proposed Model

In our study, we adapted the UNet architecture to enhance its accuracy in segmenting stroke cases in computed tomography. We introduced modifications to the classic 3D UNet model using various techniques, including data augmentation, dropout, the Adam optimization algorithm, l2 regularization, and instance normalization. Each of these methodologies brings its own undeniable benefits to the table.

Fig. 6 illustrates the proposed UNet architecture. In this neural network structure, every neuron is linked to all preceding layer neurons, each linkage carrying its unique weight factor. Within a convolutional neural network, a small weight matrix—utilized in convolution operations—is slid across the entire processed layer (at the network's input, directly along with the input image). The convolution layer aggregates the results of the element-wise multiplication of each image segment with the convolution kernel matrix. The weight coefficients of the convolution kernel remain undetermined and are set during the learning process [31].

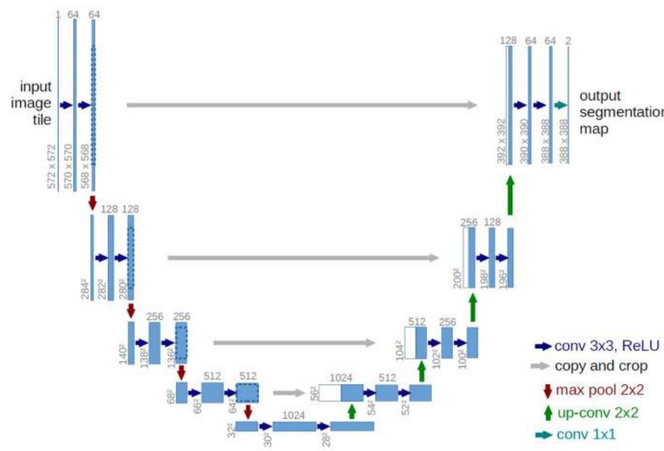

Fig. 5. UNet architecture.

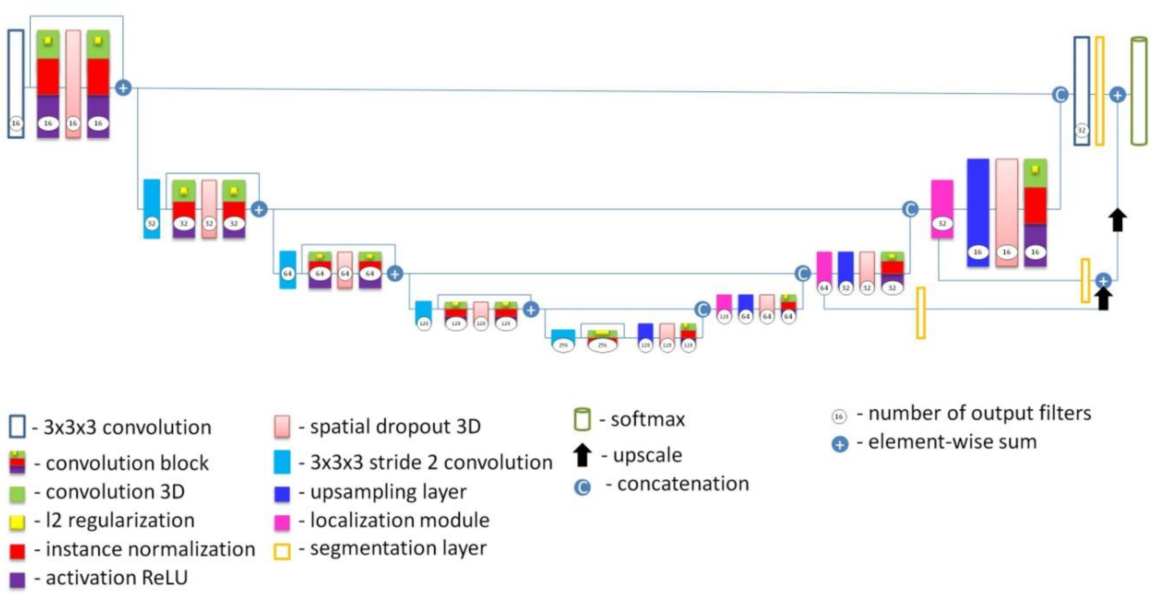

Fig. 6. Proposed enhansed UNet architecture for stroke segmentation.

Model data sizes were as follows: input shape = [5, 128, 128, 32], weight decay=0. For comparison, the classic 3D UNet was evaluated over 200 epochs, while the proposed 3D UNet model ran for 650 epochs. Upon evaluation, the classic 3D UNet model achieved a dice/f1 score of 48%, precision of 39%, recall/sensitivity of 99%, and a Jaccard index of 35% during training, while the proposed model received scores of 90%, 83%, 93%, and 89% on the same metrics, respectively. In terms of testing, the classic 3D UNet model yielded a dice/f1 score of 36%, precision of 38%, recall/sensitivity of 37%, and a Jaccard index of 32%, while the proposed model achieved a dice/f1 score of 58%, precision of 68%, recall/sensitivity of 60%, and a Jaccard index of 66%.

IV. Evaluation Metrics

In the process of evaluating the efficacy of the proposed model, we leverage several evaluation metrics.

Accuracy is an indicator that illustrates the accuracy rate of the model prediction across all parameters. It is measured as the percentage of correct predictions made by the model. This is particularly helpful in situations in which all of the classes are of similar importance. The formula for determining it is the ratio of the number of accurate forecasts to the total number of predictions made. In fact, this is the probability that the class will be predicted correctly. Eq. (1) demonstrates formula of accuracy.

$$Accuracy(a) = \frac{\sum_{i=1}^{N} \|[a(\chi_i) = y_i]}{N} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Here, TP is true positives, TN is true negatives, FP is false positives, FN is false negatives.

The Dice Similarity Coefficient (DSC), also known as the Sørensen–Dice index, is a statistical measure used extensively in image segmentation tasks, particularly for evaluating the performance of image classification models [32]. It quantifies the overlap between two binary images, usually the ground truth and the predicted output. Computationally, DSC is the twice the area of overlap between the two images divided by the total number of pixels in both images. A DSC score of 1 represents perfect agreement, while a score of 0 denotes no overlap. In medical image analysis, it aids in assessing the quality of segmentation models.

$$Dice(A, B) = \frac{2|A \cap B|}{|A| + |B|} \quad (2)$$

The Jaccard index, or Jaccard similarity coefficient, is a statistical measure widely used for comparing the similarity and diversity of sample sets. In the context of image segmentation and classification, it assesses the overlap between the predicted output and the ground truth. Computationally, it is the intersection (area of overlap) divided by the union (total area) of two binary images. The Jaccard index ranges from 0 to 1, where a score of 1 indicates perfect overlap and a score of 0 suggests no overlap. It is a critical evaluation metric in various domains, including medical image analysis, where it quantifies the accuracy of segmentation models.

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (3)$$

Precision, often referred to as the positive predictive value, is a key performance metric in statistical classification tasks, measuring the proportion of correctly identified positive instances out of all instances that the model predicted as positive. It evaluates the exactness or quality of a classifier by highlighting its false positive rate [33]. A high precision score indicates fewer false positives, meaning the model has accurately predicted the positive instances. However, precision alone doesn't account for false negatives (actual positives predicted as negative), and thus, it's usually used alongside other metrics like recall and F1-score to provide a comprehensive model evaluation.

$$precision = \frac{TP}{TP + FP} \quad (4)$$

Recall, also known as sensitivity or true positive rate, is a critical performance metric in statistical classification models [34]. It measures the proportion of actual positive cases that are correctly identified by the model. In essence, recall gauges a model's ability to find all the relevant instances within a dataset. A high recall indicates a low rate of false negatives, meaning the model has effectively captured the positive instances. However, it's worth noting that recall doesn't account for false positives (predicted positives that are actually negatives). As such, it's commonly used alongside precision and F1-score for a more holistic evaluation of a model's performance.

$$recall = \frac{TP}{TP + FN} \quad (5)$$

The harmonic mean between accuracy and completeness is denoted by the letter F-measure. If either accuracy or completeness trend towards 0, then so does this metric. Eq. (6) demonstrate formula of the F-measure evaluation parameter.

$$Fmeasure = \frac{2\,\mathrm{Pr}ecision \bullet \mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call} \quad (6)$$

V. Experimental Results

To demonstrate the functionality of the CNN classification model, a web application was created using Python along with ngrok and streamline. As shown in Fig. 7, a brain image is uploaded to the web application. Subsequently, the CNN model performs classification and provides a response based on the model's results. In this instance, the model correctly classified the image as normal with an accuracy of 79%.

Our experimental work leveraged the established U-Net architecture and the ISLES 2018 dataset. We carried out the practical portion of the experiment using the Tensorflow library within the Google Colab environment.

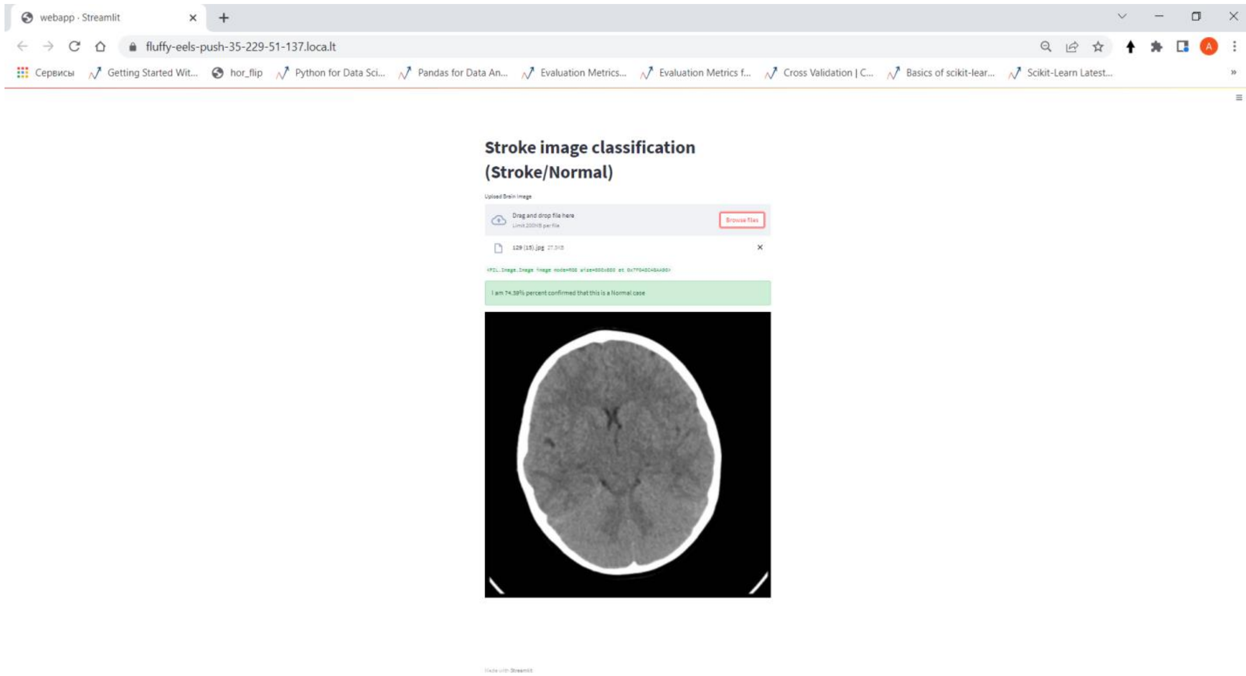

Fig. 7. Stroke classification web app on CNN model.

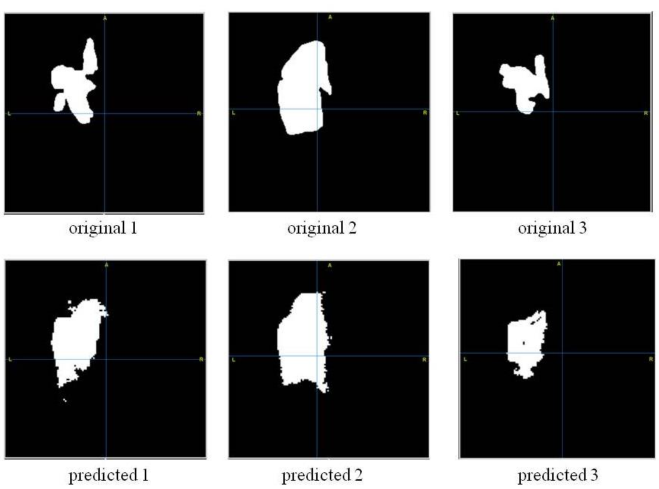

Fig. 8. Brain stroke segmentation results. (First line images are original images; Second line images are the images after applying segmentation).

Fig. 8 depict three instances of original segmented images alongside their predicted counterparts according to the proposed UNet model. Initially, the original images exhibited superior quality. However, to reduce the number of neural network parameters for computations in Google Colab, we had to resort to image compression [35]. Consequently, due to the degradation in image quality, the predicted images show deviations compared to their original versions. Nevertheless, the segmentation of the stroke lesion area was correctly identified and delineated.

VI. Discussion

In this study, we have presented a comprehensive investigation into a deep learning approach using the Internet of Medical Things (IoMT) for analyzing computed tomography (CT) brain images of stroke patients [36]. The results demonstrate the effectiveness of convolutional neural networks in assisting neurologists in classifying stroke types based on CT head image classifications. Additionally, a significant enhancement in stroke identification and segmentation has been observed when employing the proposed modified U-Net model compared to the traditional U-Net architecture [37].

The significance of this research lies not only in the achieved outcomes but also in the methodologies and techniques employed. The utilization of the 2018 ISLES dataset, one of the most comprehensive stroke visualization datasets, provides a robust foundation for analysis [38]. Moreover, the use of an enhanced deep learning model to tackle such a complex and critical task underscores the potential that artificial intelligence and IoMT hold in the realm of healthcare.

Our proposed model modifies the U-Net architecture to achieve higher segmentation accuracy of stroke regions on CT images. Yet, this study also encountered certain limitations. For example, the compression of high-quality images for Google Colab's computation requirements resulted in degraded image quality, impacting the accuracy of the predicted images. This underscores the need for advanced computational capabilities to handle high-resolution medical imaging data without compromising on quality, thus retaining the critical details needed for accurate diagnosis.

However, even with these challenges, the proposed model achieved promising results. Compared to the traditional 3D UNet model, our modified model demonstrated higher Dice/F1 scores, precision, recall/sensitivity, and Jaccard index, both during training and in test results. These metrics provide clear evidence of the model's superior performance in segmenting stroke regions in CT images.

As with any study, the future direction of this research hinges on the lessons learned. The noted constraints will serve as considerations in future research, especially in relation to data and computation requirements. The successes of this study also pave the way for more advanced deep learning and IoMT applications in medical imaging analysis [39]. Specifically, more complex and adaptable deep learning models can be explored for more precise and reliable results.

To sum up, this study illustrates the power of AI in the IoMT context to accurately analyze CT images of stroke patients. Despite its limitations, the complex system of stroke diagnosing show considerable promise and lays the groundwork for future studies in this field. It emphasizes the need for continued research and development in this area to fully realize the potential of deep learning and IoMT in transforming stroke diagnosis and treatment. As the field continues to evolve, these technological advancements will undoubtedly play a pivotal role in enhancing patient care, improving outcomes, and ultimately, saving lives.

VII. Conclusion

In conclusion, this research provides valuable insights into the integration of deep learning and the Internet of Medical Things (IoMT) within medical imaging analysis, specifically focusing on Brain Computed Tomography (CT) images of stroke patients. Leveraging the advantages of IoMT, CNN classification, and the modified U-Net model, substantial progress has been made in enhancing the accuracy of stroke detection, classification, and segmentation. This, in turn, contributes to informing the decision-making processes in stroke treatment.

However, the research also identified computational constraints and image quality degradation as challenges that need addressing in future studies. The computational power required for high-resolution medical image processing and deep learning model training, along with the necessity for maintaining the quality of original images, are aspects that future work must address to harness the full potential of AI and IoMT in healthcare.

Despite these challenges, the research underscores the transformative potential of deep learning and IoMT in healthcare. It highlights the ability of advanced AI models to deliver accurate and precise results that can potentially revolutionize the process of diagnosing and treating strokes. This study, therefore, sets the stage for further exploration and enhancement of AI models in medical imaging analysis.

In closing, the application of deep learning and IoMT in the field of medical imaging is a burgeoning area of study. With continued research and technological advancements, we are optimistic about the prospects of these tools in bringing about a paradigm shift in the diagnosis and treatment of critical health conditions like strokes, ultimately improving patient outcomes.

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