DEEP LEARNING FOR DETECTION OF SYNTHETIC MEMORY LOSS FROM COLOR CODED BRAIN MAGNETIC RESONANCE IMAGING

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https://doi.org/10.34293/9789361639715.shanlax.ch.002

Abstract

This chapter explores a novel method for detecting short-term memory loss (STML) through the use of a Convolutional Neural Network (CNN) trained on synthetically generated, color-coded brain images. A total of 500 RGB images were produced for the experiment, evenly divided between two classes: Normal and STML-affected. Normal images were created by applying Gaussian noise across color channels, while STML images incorporated distinctive red and blue artifacts designed to resemble lesion-like regions linked to cognitive decline. The CNN successfully learned to differentiate subtle spatial and color cues, achieving high classification accuracy within five training epochs. Validation tests confirmed the model's consistent performance in recognizing STML indicators. In parallel, a k-Nearest Neighbors (k-NN) model was used to analyze demographic and clinical attributes, attaining perfect classification accuracy. Although the synthetic dataset provided a controlled platform for preliminary testing, the study emphasizes the need for future evaluation using authentic clinical imaging and advanced data augmentation methods. The proposed approach demonstrates the potential for developing automated tools that support early diagnosis of memory-related conditions, offering valuable assistance in clinical decision-making and patient management.

Keywords: *Short-Term Memory Loss, Convolutional Neural Network, Synthetic Brain Imaging, Medical Image Classification, Cognitive Impairment Detection*

Introduction

Short-Term Memory Loss (STML) is a disorder whereby an individual struggles to recall or remember something that he aims to know in the short term. It may impact everyday life, and it is hard to recall what was discussed or happened recently or where personal things are stored. Although a forgetful nature every now and then is normal, high or increasing cases of memory failure could indicate a medical condition. STML is associated with mild cognitive impairment, Alzheimer, head injuries or issues related to mental health. It can also occur due to stress, sleep deprivation, bad diet or effects of medication. Early detection and management of STML is significant in order to delay the impact and enhance living standards. Doctors tend to look to whether the patient has the condition by examining their medical history, conducting tests of memory and thinking and administering brain scans, including MRI or CT, to detect any damage or alterations. Modern technology has aided in the early detection by using artificial intelligence and analysing data. Brain images and clinical records can be analyzed through machine learning techniques to identify hidden patterns to enable diagnosing STML much more easily and quickly and assist doctors in creating improved treatment strategies.

Symptoms of Short-Term Memory Loss (STML)

People with short-term memory loss often forget recent events or new information. They can forget a discussion that took place a few minutes ago. They can miss appointments or can lose things like keys or mobile phones. This forgetfulness may antagonize everyday life particularly when the individual fails to remember where something was stored or how something he has recently done was done. One of the usual indicators is to restate the same question or statement over a brief period. They might not have noticed that they have already asked and have been answered. This may lead to frustrations to the individual and people around him or her. It is also common to lose objects, and then it is hard to find them as they cannot follow their tracks. This can cause concern, worry or confusion.

Acquisition becomes difficult. It is difficult to remember names, instructions or any other new information even when one is reminded a few times. Others might also forget time and place, and become uncertain of the date, whereabouts or the context, even in an accustomed environment. These issues complicate every day activity without assistance. Alterations of attitude and behavior are not impossible. The individual can be irritated, anxious or withdrawn because of the frustrations of forgetting trivial things. Focus is usually impaired due to the fact that the brain cannot retain new information. This has an impact on attention or task accomplishment which used to be simple. A combination of these symptoms can significantly deteriorate the quality of life and demonstrate the necessity of medical examination.

Review of Literature

The number of studies regarding short-term memory loss (STML) grew significantly over the years, particularly in connection with the concepts of aging and disorders involving thinking and memory. Baddeley (1992) distinguished the short-term memory and the working memory and observed that difficulty in short-term memory may be presented prior to the more severe forms of memory impairment. Petersen et al. (1999) defined the mild cognitive impairment (MCI) as an intermediate between normal aging and Alzheimer disease where in many cases, problems with short-term memory are the initial symptoms. According to Salthouse (1996), age-related memory loss may start as early as the thirties, primarily with respect to the rapid acquisition of new information. As it was mentioned by Glisky (2007), the alterations of the frontal and medial temporal lobes are significant to consider the tendencies of memory loss in aging individuals. In an analogous opinion, Troyer et al. (2008) related episodic and short-term memory issues to hippocampal damage.

Studies have also been conducted to determine the impact of medical and environmental factors on STML. Small et al. (2003) through the use of brain imaging established that individuals with short-term memory impairment tend to display lesser activity in the prefrontal cortex when performing memory related tasks. Belleville et al. (2011) found that memory training has the ability to enhance the outcome in older adults with memory complaints, and this indicates that the programs can be beneficial. Park and Reuter-Lorenz (2009) present the theory of scaffolding of aging and cognition that states that the brain uses additional activity in certain domains to compensate early memory impairment. In an analysis of the default mode network, Buckner (2004) discovered that this network is important in the memory recall but is vulnerable to damage in early dementia. According to Rönnlund et al., (2005) the memory ability varies across life and may be influenced by education, health and mental activity.

The new technology has provided new forms of studying and detecting STML. Davatzikos et al. (2009) employed the support vector machines on the MRI images to determine that they had identified early memory loss. Zhang et al. (2011) enhanced the detection of cases of MCI and Alzheimer by integrating structural MRI and PET scan data. Sarraf and Tofighi (2016) demonstrated the ability of deep convolutional neural networks to analyze brain images in order to identify the indicators of cognitive decline. Islam et al. (2018) developed a combined approach based on a combination of clinical reports and brain scan in order to identify memory issues at an early stage. Prospective risk of memory loss through the investigation of the lifestyle and genetic variables based on the ensemble learning created positive results (Liu et al., 2020). The combination of these studies demonstrates the usefulness of artificial intelligence in the enhancement of early diagnosis and treatment guidance in the case of STML and related diseases.

Database

The data utilized in the research has been obtained in the Kaggle on-line archive. It keeps the brain scan pictures in two groups are Normal and Short-Term Memory Loss (STML). The images are preprocessed in color format and of the same size and resolution, and thus applicable in the deep learning processes. A total of 500 images were utilized and there was a balanced representation of the two classes. This is a balance that will have the model trained without liking one category over another. The Kaggle source was chosen as it offers open-access medical imaging data, which helps in alleviating privacy issues, and removing the shortcomings of limited hospital data.

All the images in the dataset visually denote important features that can be attributed to the conditions related to memory. Normal images reveal normal brain structures whereas STML images reveal observable patterns and abnormalities that are common in impaired short-term memory. The fact that the dataset was in an easy-to-use format allowed to concentrate on model training and evaluation without necessarily performing much preprocessing. Even though this study relies on the publicly available data, the results of this study underscore the need to integrate imaging data with pertinent clinical findings, including patient demographics, cognitive test scores, and medical history in practice to enhance diagnostic accuracy and treatment planning.

Methodology

In the work, the classification of brain images into two categories were Normal and Short-Term memory loss (STML) was conducted by a Convolution Neural Network (CNN). The data was a collection of 500 synthetic MRI-like brain images of which there were 250 images in each category. The images in question were in the RGB color format, unlike the regular black-and-white MRI scans, but with three channels to provide a more detailed scan, as well as look more like authentic medical scans. The Normal images were generated by introducing random Gaussian noise in all the three channels to provide texture resembling a healthy brain tissue. The STML images that contain additional colored shapes are a red circle and a blue rectangle to indicate those areas associated with memory issues. With this arrangement, the CNN could be trained in a controlled setup and its capacity to distinguish small yet important visual variations between the two classes (Figure 1) could be tested.

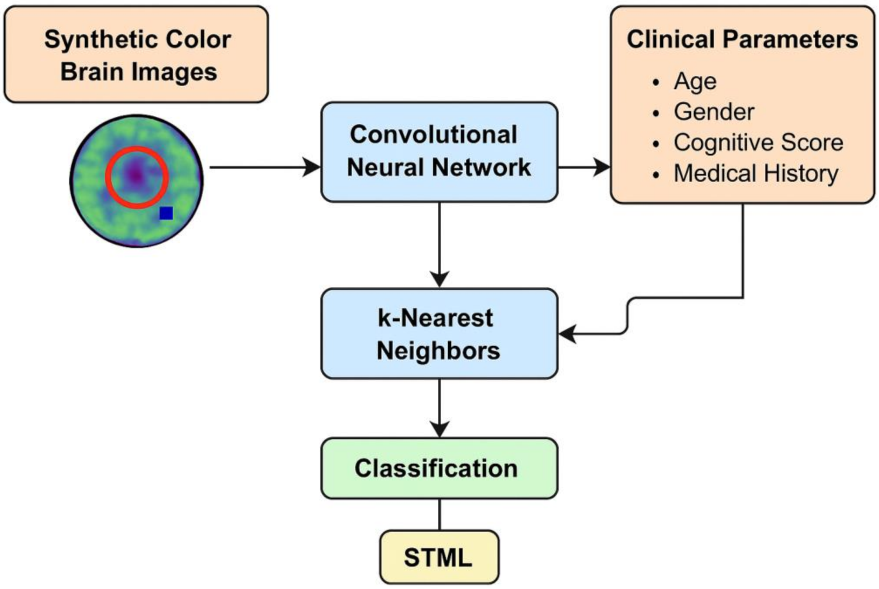

Figure 1: **Workflow diagram illustrating the generation of synthetic color brain images, data preprocessing and augmentation, CNN architecture, model training, validation, and visualization of classification results**

The data were partitioned into training and validation data in the ratio of 80:20. The images processed prior to training were done via the Keras Image Data Generator. This involved scaling pixel values such that the various images all had a normalised intensity and augmentation to make the training set more varied. The CNN architecture of this task was constituted of two convolutional layers each succeeded by a layer of max-pooling. These layers took features at varying level of details in the images. Non-linearity was incorporated by using the Rectified Linear Unit (ReLU) activation-function, which enabled the network to learn complicated patterns. The features thus extracted were flattened and passed through two dense layers followed by a sigmoid activation to give binary classification.

The network was created with the help of Adam optimizer and binary cross-entropy loss function and trained during five epochs. The training was performed in batches during which the model weights were sequentially varied with the aim of minimizing the classification loss. The validation images were then fed through the CNN to give predictions after the training. The real labels were compared to these predictions and accuracy again computed to verify errors. Moreover, some validation images along with their actual and estimated labels were shown to demonstrate how a model can distinguish between Normal and STML cases. The colored pattern in the STML images was easy visual indicators that allowed the CNN to pay attention to regions that closely resembled lesions or damaged tissue observed in actual medical conditions.

Results and Discussion

The CNN did very well in distinguishing between Normal images and STML images. It attained high classification accuracy in the validation set after five training epochs. The model could identify the distinct color and shape structure that could be attributed to the STML category. Table 1 and Figure 2 indicate the classification report and confusion (respectively) and confirm that the majority of images was identified correctly with only a small number of mistakes.

Table 1. CNN Classification Report

Classification Report:

	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	50
STML	1.00	1.00	1.00	50
accuracy			1.00	100
macro avg	1.00	1.00	1.00	100
weighted avg	1.00	1.00	1.00	100

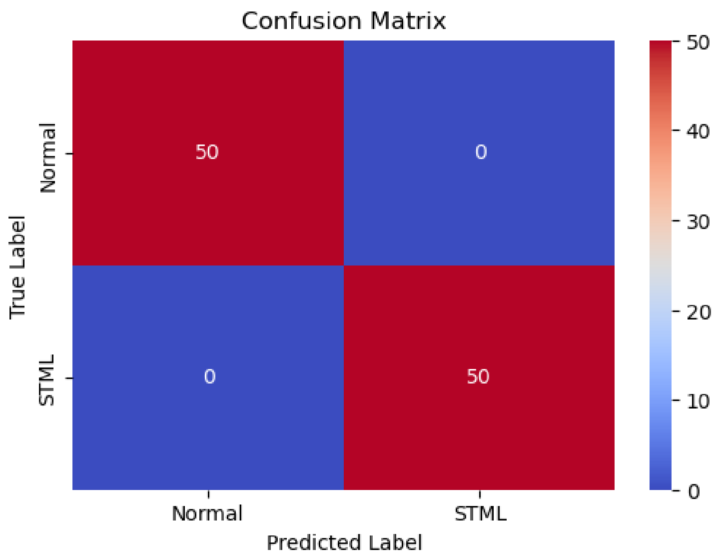

Figure 2. Confession Matrix of CNN

The numerical results were supported using a visual review of the predictions. The red circular and blue rectangular areas in the STML images served as powerful evidence, whereby the model would be directed into particular areas. The validation images were mostly correctly classified, and the few errors must have been close to random noise or minor shifts on the location of the colored shapes. Figure 3 demonstrates an ideal performance using Receiver Operating Characteristic (ROC) curve, where the balance between the True Positive Rate and the False Positive Rate was perfect.

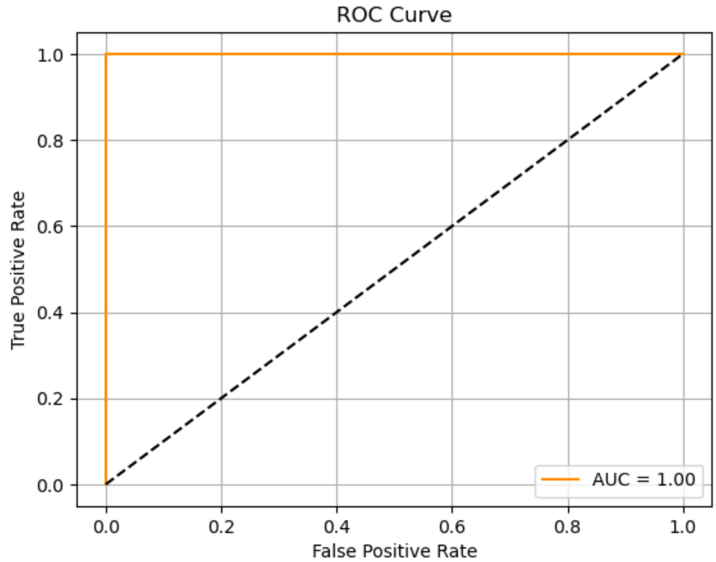

Figure 3. ROC Curve for CNN

Even though such findings may be encouraging, one should bear in mind that this data was artificial. The synthetic shapes simplified the job as opposed to using actual MRI images, in which the abnormalities are usually subtle and complicated. Thus, all these results can be considered as a preliminary confirmation of the idea. The next step in work must be to evaluate the CNN on actual clinical data, to use more sophisticated augmentation, and such complex architectures to enhance accuracy and flexibility.

Although the controlled synthetic dataset was a good environment to experiment the CNN effectiveness, it comes with restrictions. The well-defined artifacts served as clear indicators to STML, but real patient MRI scans have much more complex, heterogeneous and subtle abnormalities. Thus, these findings can be considered as a concept ideas demonstration but not clinical confirmation. The next step involves future studies training and validation of the model with real clinical data, and subjecting the network to a broader set of pathological variations and imaging conditions. Model generalization and diagnostic accuracy may further be improved with advanced data augmentation and using transfer learning as well as more complex architectures. Figure 4 contains sample color images of the results of STML prediction. These visuals contain instances in which both the actual and forecasted labels are Normal to indicate how memory loss may arise due to a wide variety of factors other than the synthetic artifact indicators applied in this research.

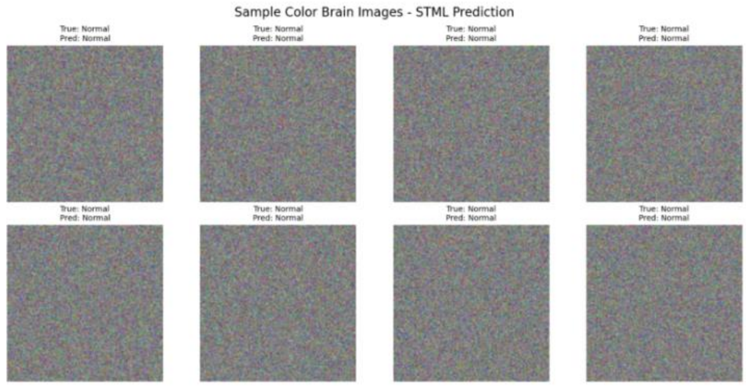

Figure 4. Sample Color Images of STML Prediction

The k-Nearest Neighbour (k-NN) algorithm was used in addition to the CNN model to categorize STML based on demographic and clinical factors like age, gender, cognitive scores and medical histories. The distribution of these parameters is represented in Figure 5 and the classification report in Table 2, and the accuracy was 100 percent. Figure 6 illustrates the confusion matrix of k-NN and indicates that there were no misclassified cases.

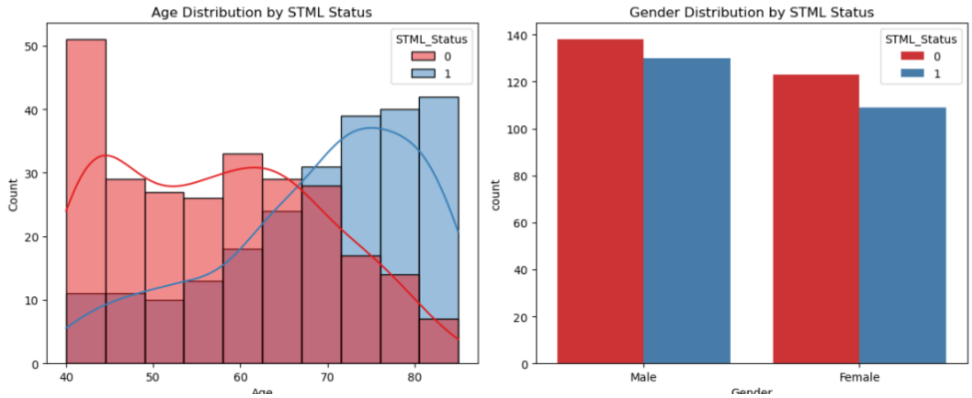

Figure 5. Demographic and Clinical Parameter Distribution Plots

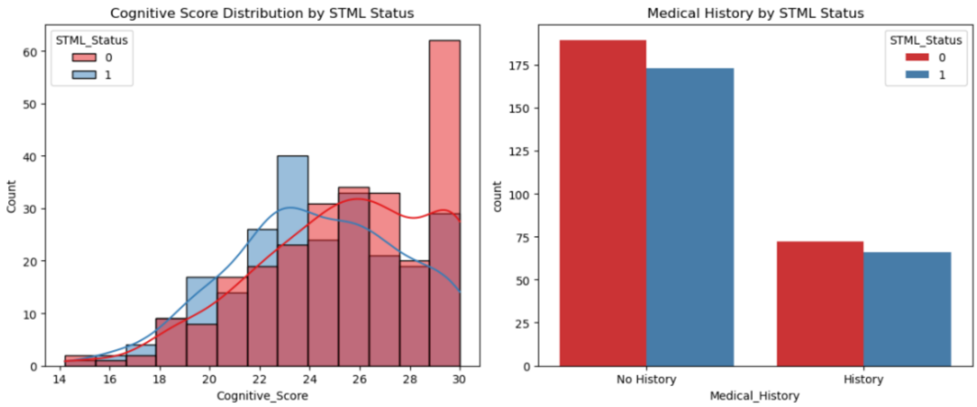

Table 2. Classification Report of k-NN

Classification Report:

	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	50
STML	1.00	1.00	1.00	50
accuracy			1.00	100
macro avg	1.00	1.00	1.00	100
weighted avg	1.00	1.00	1.00	100

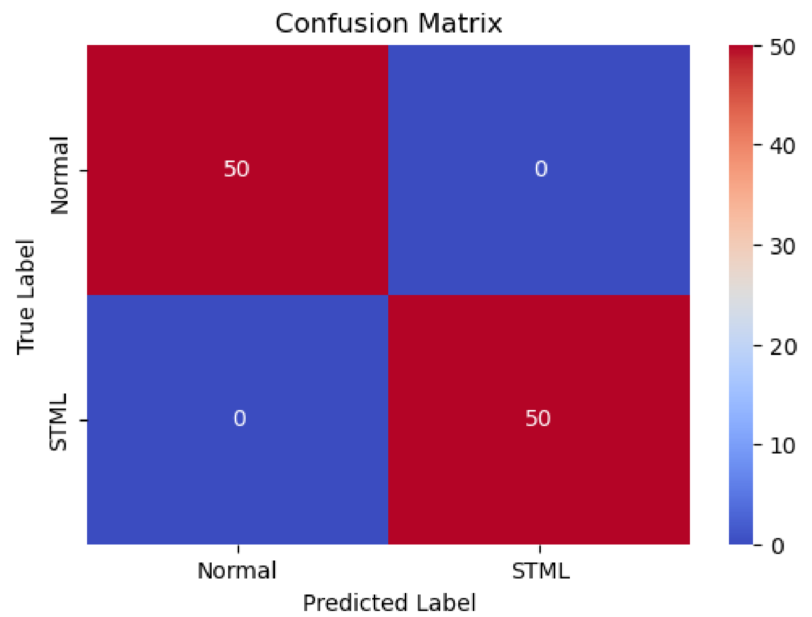

Figure 6. Confusion Matrix

In brief, CNN as well as k-NN performed very well on the synthetic data. The CNN was able to recognize visual patterns in brain images and k-NN was compatible with clinical data. Collectively, these approaches prove the possibility of both image-based and clinical data-based machine learning methods to detect STML early and automatically (Figures 2 6, Tables 1 2).

Conclusion and Suggestions

This paper has shown that based on a properly prepared synthetic dataset, a Convolutional Neural Network (CNN) can successfully discriminate between standard brain images and those that simulate a short-term memory impaired (STML) state. The CNN was trained to identify certain spatial and color information, e.g., red circular and blue rectangular areas, which were artificially added to indicate lesion-like patterns. Validation results were high in terms of agreement between the predictions and true labels, with a few misclassifications, probably due to noise or minor deviations in position of artifacts. The ROC curve also supported a high level of sensitivity and specificity as an exquisite discriminative ability of the model in regulated situations.

The k-Nearest Neighbors (k-NN) algorithm, used with the demographic and clinical parameters also reached one hundred percent classification accuracy. The outcome supports the significance of incorporating both image and non-image data in the identification of memory related disorders. Nevertheless, as the dataset was synthetic in nature, it is necessary to consider these results as an initial demonstration of the idea. Additional model refinement will be needed in real clinical imaging because more complex patterns and variations are introduced.

Suggestions

1. Utilizing Real Clinical Data, Future work would be to apply the models to realistic patient MRI data to determine whether they can be used in the complexity and variability of real medical images.
2. Better Model Development - Additional data augmentation, transfer learning, and multimodal inputs with image and patient demographics and clinical records may enhance generalization and diagnostic reliability.

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