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**INTEGRATIVE AI APPROACHES FOR MENTAL
AND VISUAL HEALTH MONITORING**

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Chapter 1

Introduction

The human eye has long fascinated scientists and clinicians. Maybe because it has an intricate structure and essential role in vision, but it is also correlated with a broader health status. The retina should be imagined not simply as a sensory tissue, but as a window in which early indicators of ocular or neurological health can be observed. Retinal diseases represent a significant global health challenge. Because of their growing frequency, the complexities correlated with their precise diagnosis, and their potential severity, including irreversible vision loss, medical professionals have tried to seek innovative diagnostic solutions. Central among these cutting-edge methods is artificial intelligence (AI), particularly deep learning (DL). The way in which DL evolved reshaped the ophthalmology domain as it has improved diagnostic accuracy, speed, and clinical efficiency.

Convolutional Neural Networks (CNNs) were initially used as AI-based ophthalmic imaging tools. They proved to be highly effective in analyzing retinal images, especially for those obtained through Optical Coherence Tomography (OCT), in view of their ability to detect subtle, localized features. However, one limitation is related to their specific view of images as they lack the understanding of a broader context of the image. The advent of Vision Transformers (ViTs) represented a significant step forward in this domain. ViTs offer a more holistic perspective because they model global spatial relationships, which addresses one of CNNs' major challenge. Therefore, hybrid models appeared that integrate CNNs' capability in local feature recognition and ViTs' abilities for global structures. The second chapter of this thesis presents the potential, advantages, and constraints of CNNs, ViTs, and their hybrid combination in the context of retinal disease diagnosis.

The focus of the thesis further shifts to the neurological implications correlated with the retina, highlighted in the third chapter. As it is often described as the "window to the brain," the retina is recognized to share embryological and anatomical connections with the central nervous system (CNS). This structural and functional similarity allows it to serve as a non-invasive marker of neurological health. Recent progress in retinal imaging modalities (OCT and OCT Angiography (OCTA)) has enhanced clinicians' ability to view small-scale retinal alterations associated with various neurological disorders, including Alzheimer's disease (AD), Parkinson's disease (AD), multiple sclerosis (MS), and schizophrenia. Such developments can help clinicians in early identifying and monitoring neurological disorders.

Despite its promise, this research is just at the beginning. Retinal biomarkers do not offer yet sufficient diagnostic accuracy for neuropsychiatric conditions like schizophrenia. These limitations highlight the need for a more holistic healthcare. The need for integrated healthcare strategies capable of providing continuous, real-time patient monitoring and disease management is continuously increasing. Chapter four explores remote health monitoring solutions, focusing on how wearable technologies and IoT platforms, when powered by AI, can enhance care delivery. These innovative tools offer continuous patient engagement, real-time symptom tracking, detailed analysis of disease progression, and timely interventions, especially for one focused psychiatric disease, namely schizophrenia. The importance of also correlating dietary habits in schizophrenia into a remote healthcare monitoring system further expands the need for integrated treatment approaches. Moreover, as schizophrenia is directly correlated with brain connectivity, the electroencephalogram (EEG) is considered an important asset into neuro-monitoring of this disease. As it is a cost-efficient and reliable tool, the EEG has been widely used in research for neuropsychiatric diseases detection and management. This chapter also addresses AI-based algorithms for schizophrenia detection using EEG data. The integration of these AI models can further augment the capabilities of a remote healthcare monitoring system.

This thesis aims to address the integrative AI approaches for mental and visual health monitoring in order to extend neurology and psychiatry domains and to also correlate them with the ophthalmology sector. Correlating advanced technological implications with practical healthcare application supports this research in visualizing a promising future in medicine. A continuous patient monitoring, precise diagnostic techniques, and proactive healthcare management come together to redefine clinical practice and patient outcomes.

1.1 Presentation of the field of the doctoral thesis

This doctoral thesis is positioned at the intersection of advanced AI techniques integrated into ophthalmology, neurology and psychiatry. It aims to explore how AI methodologies, particularly DL, can revolutionize diagnostic practices within ophthalmology, having an impact in the detection and management of retinal diseases. Among the DL-based algorithms, CNNs and ViTs have been used in retinal disease detection.

This thesis further examines the retina's anatomical and embryological connection to the CNS, positioning retinal imaging as a promising approach for the early detection and management of neurological and psychiatric disorders. OCT and OCTA retinal imaging techniques may enable visualization of small retinal changes linked to various neurological conditions, including AD, PD, MS, and schizophrenia. However, this also can lead to limitations in complex neurological diagnostics using retinal imaging which this thesis address. Thus, comprehensive remote healthcare

monitoring solutions that encompass AI, wearable technology, IoT, and EEG data are also considered in order to have a broader view of the patient care.

These directions propose to define an innovative field of study aimed at redefining diagnostic practices, improving patient outcomes, and transforming healthcare paradigms across multiple medical domains.

1.2 Scope of the doctoral thesis

This thesis explores how advanced AI can be used to improve diagnostic accuracy in both retinal imaging and EEG analysis. One scope is to identify the AI architectures that balance high diagnostic accuracy with practical clinical applicability, while also considering important aspects such as computational efficiency and real-world feasibility.

The thesis also aims to address the retina's role as a predictive tool for broader neurological and psychiatric disorders and it also addresses the practical integration of AI for dietary-related habits of individuals with schizophrenia. Therefore, the thesis aims to connect theoretical AI research with real, usable insights that could reshape patient care in fields where early, accurate detection is critical.

1.3 Content of the doctoral thesis

This doctoral thesis is structured into three main chapters, each building upon the previous one to offer a comprehensive exploration of AI-driven healthcare innovation. The second chapter, “*Artificial Intelligence in Retinal Disease Detection*,” investigates the application of advanced DL models, including CNNs, ViTs, and hybrid architectures, to improve the diagnostic accuracy of retinal disorders. This chapter provides an in-depth evaluation of these models, discussing their strengths, limitations, and potential integration into clinical practice.

The third chapter, “*Retinal Imaging as a Window into Neurological Health*,” expands upon the insights from ophthalmology to explore the broader neurological significance of retinal biomarkers. This chapter examines the anatomical and functional correlations between the retina and CNS, reviewing state-of-the-art retinal imaging techniques to identify early indicators of neurological diseases. It also highlights several statistical approaches that are applied on a small dataset in order to emphasize the tight correlation between schizophrenia and the retina.

The fourth chapter, “*Remote Healthcare Monitoring of Psychiatric Patients*,” further expands on the thesis content. It delves into practical applications of AI and IoT technologies in remote patient monitoring, especially for schizophrenia patients, using EEG data. It discusses technological innovations, patient management strategies, and

real-world challenges, emphasizing how these AI-driven solutions can enhance clinical outcomes and patient quality of life across psychiatric care settings.

Chapter 2

Artificial Intelligence in retinal disease detection

This chapter presents how the retina works and the importance of early diagnosis of retinal diseases. It also underscores the role and potential of CNNs, ViTs and their hybrid models in retinal disease detection, providing a thorough perception of their capabilities, advantages, and limitations. One challenge is considered the computational resources required for the implementation of the transformer-based architectures. That is why, hybrid approaches that integrate CNNs with ViTs have obtained significant research interest as they make use of the ability of local feature extraction from CNNs as well as the capacity of global context analysis provided by ViTs. Thus, the exploration of AI's role in ophthalmology opens interesting possibilities for deeper medical insights.

2.1 The anatomy of the retina & how the retina works

The human eye is not just an organ of sight, but it is a complex structure central to how we perceive and interact with the world. The light first enters the eye through the pupil and it is further regulated by the iris, whose pigmentation defines eye color based on melanin concentration. The passage of light through the cornea and crystalline lens ensures accurate focusing onto the retina, where visual signals are initiated. These structural components are critical for image formation and they also illustrate the sophisticated engineering of the eye in adapting to changing light conditions.

2.1.1 Development of the eye

The development of the human eye starts even before birth, during the embryonic phase. The optic vesicles fold back to generate the optic cup, where the inner layer converts as the retina and the outer layer develops into the retinal pigment epithelium (RPE). As the retina develops, its cells migrate and differentiate, resulting in the formation of a complex and layered structure. In the fifth month of gestation, the fundamental neural structure of the retina is formed, paving the way for the development of functional synapses and the maturation of photoreceptors cells. The

final phase in this journey is the maturation of the fovea, which persists until around four years after birth. This ensures that the eye is completely prepared to perceive the complexity of the visual environment.

2.1.2 Anatomy and physiology of the retina

The human retina is a complex structure which continues the story of the eye. It is considered the essential interface between the incoming light and the visual perception formed in the brain. It measures barely over 0.5 millimeters in thickness and it covers the inner surface of the eyeball. The retina is divided into three distinct layers, each consisting of different types of nerve cells. The layers (Figure 2.1) are interconnected through synaptic areas which facilitate the communication between cells. The external layer of the retina, positioned at the back of the eye, contains the photoreceptors (rods and cones), responsible for gathering the light and starting the visual process. The position of the photoreceptors requires the light to pass through the entire retinal structure before reaching the rods and cones.

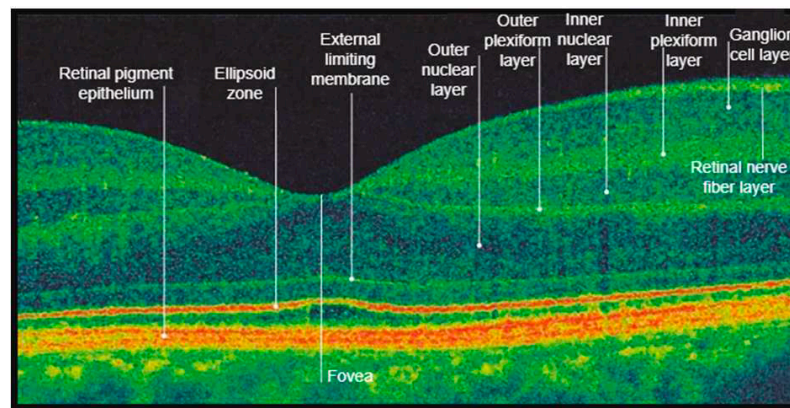


Figure 2.1 An OCT scan and the retinal layers (adapted from David Turbert)

2.2 Overview of retinal diseases and current diagnostic methods

Given the retina's complex structure and central role in visual processing, any pathological changes can significantly impair vision. Retinal diseases are among the top global causes of vision loss and blindness, and conditions such as Age-related Macular Degeneration (AMD) and Diabetic Retinopathy (DR) are particularly prevalent. Timely diagnosis of these diseases is essential to prevent irreversible damage and improve quality of life.

AMD is highlighted as a leading cause of irreversible central vision loss in individuals over 50. It primarily affects the macula, the region responsible for fine detail perception, often progressing silently in its early stages. AMD exists in two main forms: dry (non-neovascular) and wet (neovascular). While dry AMD accounts for the majority of cases, wet AMD leads to the most severe visual impairments due to abnormal blood vessel growth and leakage beneath the retina. The formation of drusen,

yellow lipid-protein deposits, serves as an early biomarker for AMD progression. Multiple risk factors (from aging and genetics to lifestyle and systemic conditions) contribute to the disease, with projections indicating a significant rise in AMD cases in the EU by 2050.

DR is the most common eye-related complication of diabetes, affecting approximately one-third of diabetic individuals worldwide. It results from prolonged hyperglycemia, which damages retinal microvasculature and can lead to vision-threatening complications such as diabetic macular edema (DME), retinal hemorrhages, and neovascularization. DR is typically categorized into non-proliferative (early) and proliferative (advanced) stages. DME can occur at any stage and often leads to symptoms like blurred and distorted vision (metamorphopsia), which significantly affects patients' daily activities. The risk of DR increases with poor glycemic control, hypertension, obesity, and smoking.

Advanced imaging techniques like OCT and fundus photography enable early detection of AMD and DR by revealing structural retinal changes before symptoms arise. Integrating these tools with AI enhances diagnosis, supports personalized care, and helps address the growing burden of these diseases in aging and diabetic populations.

2.3 DL in retinal imaging

DL have been applied to color fundus photography, OCT scans or autofluorescence imaging for diagnosing and tracking various retinal diseases like DR, AMD, or retinopathy of prematurity as well as for detection of various conditions ranging from retinal vein occlusion or retinal detachment to hereditary retinal disorders, such as retinitis pigmentosa.

With a structural capacity of simplifying the diagnostic workflow, DL algorithms can deliver highly reliable predictions, being an active support for the medical decision-making processes. To fully comprise the progress made into this domain, this sub-chapter is designed to present the evolution of the most recent techniques, from foundational DL algorithms to the advanced ViTs.

2.3.1 State of the art in fundus imaging and OCT/OCTA segmentation algorithms

DL has significantly advanced the field of retinal imaging by enabling automated, high-precision analysis of fundus and OCT/OCTA data. Leveraging architectures such as U-Net and its modern adaptations, DL models excel at segmenting complex retinal structures and pathological features, including blood vessels, optic discs, drusen, and exudates. These models reduce reliance on manual interpretation while maintaining high levels of accuracy and consistency. Beyond segmentation, DL-based classification models can assess disease presence or progression, with hybrid models combining both tasks to enhance diagnostic value. Recent innovations, such as Swin-Transformer-based networks and hybrid CNN-ViT frameworks, integrate multi-scale attention

mechanisms and hierarchical feature extraction to improve performance. Benchmark comparisons across diverse datasets demonstrate that these tailored DL techniques not only outperform traditional methods but also offer scalable, efficient solutions for clinical and research applications in ophthalmology.

2.3.2 State of the art in fundus imaging and OCT/OCTA classification algorithms

Various AI models and architectures improve the performance of medical imaging analysis, being recently used in the classification in ophthalmology. The CNNs have been widely used for the automatization of this process as they have proved strong capabilities in image processing tasks, including feature extraction which is a mandatory step in rendering complex retinal images. ViTs are also considered as state-of-the-art in this domain since they showed great abilities in extracting spatial features within images for depicting more thorough information. Besides these 2 categories, there are also more variants that have been applied for classification tasks in retinal fundus imaging and OCT/OCTA.

2.4 Case studies and applications in retinal disease detection

2.4.1 Datasets

There were two datasets that were used in this thesis: Kermany [65] and NEH datasets [66]. The Kermany dataset that was used in this research has 84,495 OCT images divided into four categories: CNV, drusen, DME and normal. The distribution among the classes in the dataset is unequal, considering the following division: CNV: 37,455 images; DME: 11,598 images; Drusen: 8,666 images; Normal: 26,565 images. The NEH dataset was mainly used for testing the algorithms on different images, a limitation being the fact that it does not contain images with DME.

The Kermany dataset is a comprehensive collection of labeled OCT images, widely utilized in the development and evaluation of DL models for retinal disease classification. This dataset was introduced by Daniel Kermany and colleagues in their 2018 study [65]. An image from each class from the Kermany dataset is presented below (Figure 2.2). The blue arrows indicate the retinal structures associated with the described disorders.

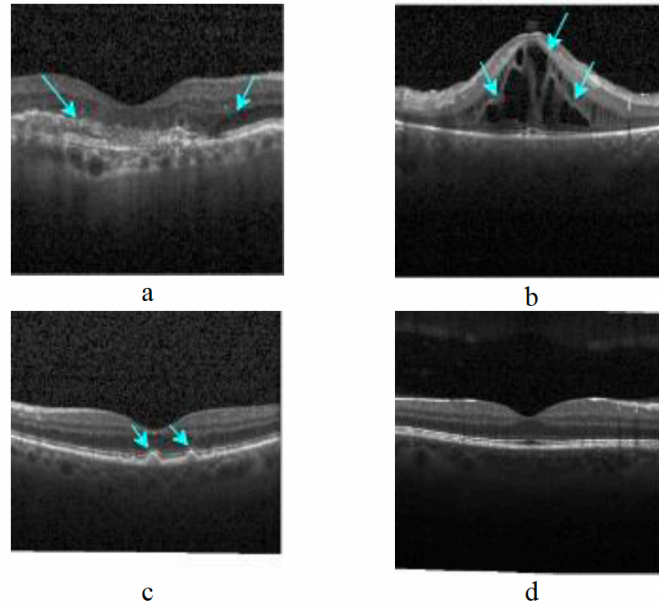


Figure 2.2 A representative image for: a). CNV; b). DME; c). Drusen; d). Normal (adapted from D. S. Kermany et al.)

2.4.2 DL models applied for OCT classification

2.4.2.1 CNN-based models

CNNs have proved their efficiency in capturing local features, which help in detecting subtle structural details. They mostly rely on localized filters and hierarchical processing, so they often miss long-range spatial relationships. In this case, the use of CNNs can have repercussions in differentiating between retinal conditions that may require a global view of the image.

Table 2.1. Performance results of DenseNet variants, Inception-ResNet and CNN-based models

Model	Accuracy	AUC	f1-score	Loss
DenseNet121	95.56	0.996	0.94	0.11
DenseNet169	97	0.997	0.97	0.1
DenseNet201	96	0.997	0.96	0.12
Inception-ResNet	93.18	0.99	0.93	0.18
12 CNN-based model	93	0.95	0.93	0.20

2.4.2.2 ViT-based models

In contrast, ViTs bring a new approach by using self-attention mechanisms that process images as sequences of patches. This allows them to capture the overall context and subtle patterns across an entire image. In order to function properly, ViTs also generally demand larger datasets and more computing power. Even with extended versions like DeepViT, the task can lead to overfitting when dealing with noise or variability in the

data. A visualization of how ViT architecture is applied on an OCT image is illustrated in Figure 2.6.

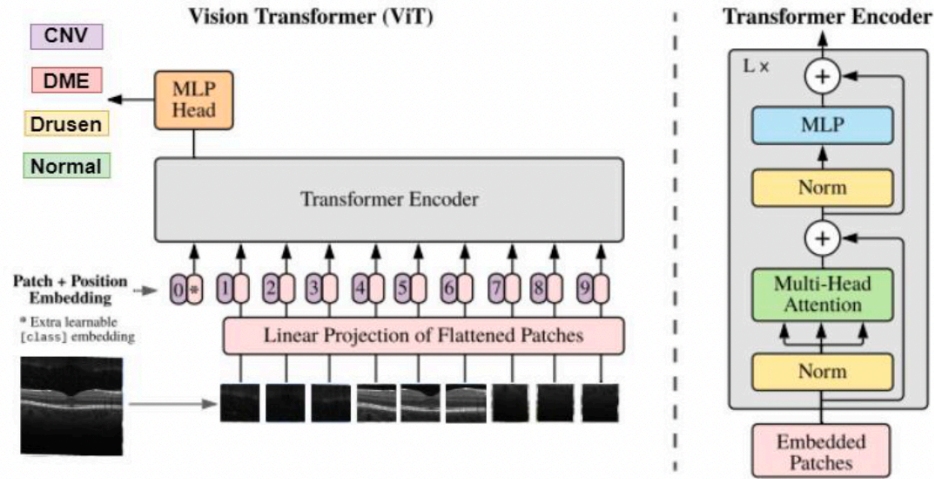


Figure 2.3 ViT architecture (adapted from Dosovitskiy, Alexey, et al.)

Hybrid models have been developed that combine the strengths of both CNNs and Transformers. The presented models (ResNet50-ViT and FusionViT) provide the integration of local feature extraction associated with the capabilities of CNNs with the global context modeling related to Transformers.

The ResNet50 + ViT hybrid model combined the local feature extraction capability of CNNs with the applicability of global pattern recognition of the Transformer. It achieved the highest accuracy (99.97%) and a good generalization across retinal disease classes. However, the computational complexity posed a significant limitation for resource-constrained environments. This challenge caused the development of the FusionViT model, which substitutes ResNet50 with a lighter convolutional backbone. This architecture reached a good balance between performance (97.83% accuracy) and computational efficiency.

In the table 2.10, there are all the models that were implemented in this thesis.

Table 2.2 Comparison table for all the models applied for retinal diseases classification

Model	Architecture	Accuracy (%)	Strengths	Limitations
DenseNet121	CNN	95.56	Efficient feature reuse, reduces overfitting	Limited long-range dependency modeling
DenseNet169	CNN	97	Deeper feature extraction, better generalization	Increased training time
DenseNet201	CNN	96	Best among DenseNet models, strong	High computational cost

			feature propagation	
InceptionResNet-V2	Hybrid (Inception + ResNet)	93.18	Multi-scale feature extraction, residual learning	Computationally intensive
CNN-based model	CNN	93	Simpler architecture, optimized for efficiency	Limited ability to capture complex patterns
ViT	Transformer	96.80	Captures global dependencies, excels at complex pattern recognition	Requires large dataset, computationally expensive
DeepViT	Transformer	89.98	Enhanced feature learning, better generalization	Overfitting risk, long training time
ResNet50 + ViT	Hybrid (CNN + Transformer)	99.97	Best accuracy, combines CNN's local feature extraction with ViT's global context	Complex model, requires significant resources
ConvBackBone + ViT	Hybrid (CNN + Transformer)	97.83	Efficient, balances performance and resource requirements	Slightly lower accuracy than ResNet50-ViT

The extensive experiments comparing CNNs, ViTs, and hybrid approaches for retinal disease classification using OCT images revealed several important aspects. On one hand, traditional CNN architectures such as DenseNet and InceptionResNet were very good at capturing fine details, but struggle with modeling long-range spatial dependencies. On the other hand, ViT and its extended version DeepViT used self-attention to comprehend the overall image context, though they tend to be resource-intensive and demand large amounts of data. Among the hybrid approaches, models such as ResNet50-ViT and FusionViT offered a promising compromise. The ResNet50-ViT model achieved the highest accuracy (99.97%), but its demand for computation load may limit its use in environments with limited resources. In comparison, FusionViT provided competitive accuracy (97.83%) with a considerably lower computational cost. This can make it more practical for real-time clinical applications.

Chapter 3

Retinal imaging as a window into neurological health

The human eye is considered as more than just an organ responsible for vision. It is an extension of the brain itself, slightly revealing insights into the neurological health. Building on the insights provided by detecting retinal diseases using DL models, as discussed in the previous chapter, this section explores in greater depth the interesting relationship between the retina and various neurological disorders.

Often described metaphorically as the “window to the brain,” the retina develops embryologically as an integral part of the central nervous system (CNS). It closely mirrors the brain’s intricate neural structure and its fine microvascular networks. This special anatomical and functional connection presents researchers and clinicians with an extraordinary opportunity: to non-invasively monitor neurovascular and neurodegenerative changes occurring within the brain through retinal examination.

This chapter highlights the idea that the subtle signs passed through the retina might significantly transform, in the future, the way of diagnosing and managing neurological health. This approach could lead to better clinical decision-making and support more effective remote monitoring of patients.

3.1 AI in detecting neurological diseases via retinal imaging

3.1.1 Alzheimer’s disease

Dementia is a profound neurological disease that seriously impair the memory, the ability to think, and the capacity to perform normal activities. Age is considered the primary risk factor conducting to AD which is the most widespread type of dementia, contributing to 60-70% of all cases.

AD is currently diagnosed based on the analysis of cerebrospinal fluid (CSF) and imaging biomarkers. However, CSF is invasive, MRI and PET are costly, and typically available only in specialized clinics, which hinders their applicability for

extensive screening. Due to these challenges, there is a high demand for non-invasive and easily accessible techniques for the early detection of AD. A promising direction involves exploring retinal biomarkers considering the connection between the retina and the CNS as they both share the same structural and functional features (blood-brain barrier, neurotransmitter system).

The analyzed literature emphasizes the diversity of retinal biomarkers and their importance towards the identification of AD based on retinal imaging techniques:

- Structural biomarkers: Ganglion Cell-Inner Plexiform Layer (GC-IPL) and Retinal Nerve Fiber Layer (RNFL) thinning;
- Retinal vascular changes: diminished vascular density, changes in capillary flow dynamics, or disrupted blood flow patterns, potentially reflecting cerebrovascular alterations in neurodegeneration process;
- Radiomic features: different attributes such as Foveal Avascular Zone (FAZ) shape, compactness or eccentricity which may improve the diagnostic insights for AD.

3.1.2 Multiple Sclerosis

Multiple Sclerosis (MS) is a chronic neurodegenerative disease characterized by multiple physical disabilities, vision loss, cognitive decline, neural myelin loss, axonal degeneration, neuronal atrophy, and inflammation at the central nervous system (CNS) level. As the retina is a component of the CNS, with two-way connections to the brain, it is commonly affected by MS (and vision loss is the initial symptom of MS for many people), almost half of these patients encountering at least one optic neuritis (ON) episode. Therefore, retinal imaging, especially the OCT technique, is emerging as a faster and noninvasive alternative for MS diagnosis. Along with this, there has recently been significant interest in the use of ML and DL-based applications for retinal imaging in tracking MS' progression.

3.1.3 Parkinson's disease

Parkinson's disease (PD) is a neurodegenerative disorder affecting over 8.5 million people globally, primarily those over 60. Beyond motor symptoms like tremors and rigidity, PD often involves early retinal abnormalities. Studies show that signs of dopaminergic dysfunction and synuclein accumulation can be detected in the retina before brain symptoms appear. OCT imaging has proven valuable in identifying retinal changes linked to PD progression and visual hallucinations. Key biomarkers include reduced thickness and volume in retinal layers such as the macula, RNFL, GCL, IPL, and photoreceptor layers, highlighting the potential of retinal imaging for early PD detection and monitoring.

3.1.4 Autism

Autism spectrum disorder (ASD) is linked to atypical brain development affecting perception, learning, and social interaction. Studies have found retinal changes in ASD, such as RNFL thinning and larger optic disc features, indicating that retinal metrics may support diagnosis. Given that retinal imaging is non-invasive and child-friendly, it holds promise for ASD assessment. However, research in this area remains limited. One study using an SVM classifier on retinal features from 46 ASD and 24 healthy children reported high diagnostic performance, with 95.7% sensitivity and 91.3% specificity.

3.2 Retinal biomarkers and AI detection in schizophrenia

AI-based retinal imaging has shown strong potential for detecting neurological disorders such as Alzheimer's, Parkinson's, multiple sclerosis, and autism. Since the retina reflects brain changes, its structural and vascular features can serve as non-invasive, cost-effective biomarkers. With the support of AI, subtle alterations can be quantified with precision, enhancing early diagnosis and monitoring.

Building on this, the chapter explores AI-driven retinal analysis for psychiatric disorders, focusing on schizophrenia (a complex mental illness affecting perception, behavior, and cognition). With a global prevalence of 0.7–1%, schizophrenia often shows early retinal changes. AI-enhanced retinal imaging may support early diagnosis and offer a new approach to managing both neurological and psychiatric conditions.

3.2.1 Visual processing changes in patients with schizophrenia

People with schizophrenia often experience visual disturbances, such as distorted shapes, colors, or even hallucinations. Beyond these perceptual changes, research shows that the disorder also affects basic visual processing, like contrast sensitivity and detail recognition, highlighting its impact on how the brain interprets visual input. In addition to cognitive and emotional symptoms, schizophrenia influences multiple senses, including vision. Retinal changes may explain some visual difficulties, which can be worsened by co-existing conditions like diabetes or high blood pressure. These connections support the potential of retinal imaging as a tool for monitoring and understanding schizophrenia.

3.2.2 Retinal alterations in schizophrenia

The retina, as an extension of the CNS, shares numerous neurobiological characteristics with the brain, making it a compelling site for identifying biomarkers associated with neuropsychiatric disorders such as schizophrenia. OCT studies have revealed thinning of specific retinal layers (e.g., RNFL, GCL, IPL, INL, ONL), macular volume reductions, and larger optic cup-to-disc ratios, all potentially reflective of underlying

neurodegeneration and treatment responsiveness. Electroretinography (ERG) findings further support functional deficits, showing diminished a- and b-wave amplitudes, particularly in rods and cones, not only in schizophrenia patients but also in their unaffected offspring, suggesting potential endophenotypic markers.

Additionally, OCTA has uncovered microvascular changes such as reduced vessel density, FAZ enlargement, venular dilation, and altered perfusion dynamics. These findings collectively point to disrupted retinal blood flow, possibly linked to neurovascular dysfunction. While these retinal biomarkers offer a promising window into schizophrenia pathophysiology, their integration into diagnostic frameworks is still in early stages.

3.3 Use case on private OCTA imaging dataset of schizophrenia patients

Recent studies highlight the growing use of retinal imaging, particularly OCTA, as a non-invasive tool for detecting neurological conditions through microvascular changes. Despite its potential, AI applications for schizophrenia detection using retinal data remain limited.

3.3.1 Dataset

The dataset for this study was provided by University of Rochester, comprising a distinctive collection of OCTA images and corresponding OCT scans from individuals with schizophrenia and healthy control (HC), annotated by Dr. Steven Silverstein who is a Professor of Psychiatry, Neuroscience, and Ophthalmology at the University of Rochester Medical Center. Each image from the dataset is also labeled with “OD” (right eye) or “OS” (left eye).

There are the following four categories in the dataset:

- Younger controls: 38 images; healthy individuals, used as reference for normal retina;
- First-episode psychosis (FEP): 18 images; recently diagnosed patients with schizophrenia, used as an early identification for this condition;
- Older controls: 34 images; healthy older adults, selected to consider how normal aging impacts the retina;
- Chronic: 23 images; long-term schizophrenia subjects, where it is most likely to underline specific neurovascular changes.

An image from each class is shown below (Figure 3.1).

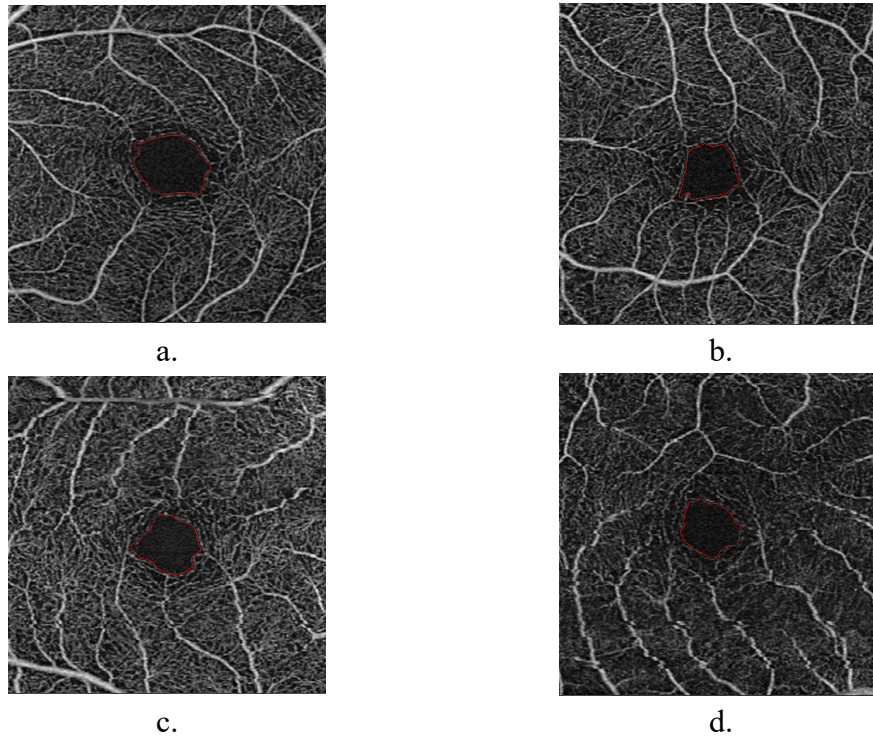


Figure 3.1 OCTA images from: a. Younger controls; b. FEP; c. Older controls; d. Chronic.

3.3.2 Statistical approach and results

This analysis investigates whether the FAZ area differs between schizophrenia patients and HCs, and whether these variations reflect disease progression. FAZ measurements were extracted from OCTA images using a customized segmentation pipeline that involved grayscale conversion, Otsu thresholding, contour detection, and pixel-to-millimeter area conversion.

The resulting distributions were compared across four groups: younger controls, older controls, FEP, and chronic schizophrenia. As illustrated in Figure 3.2, the boxplot visualization clearly highlights an upward shift in FAZ area values for chronic schizophrenia, compared to all other groups, supporting the hypothesis that retinal microvascular changes are more prominent in the later stages of the disorder. In contrast, FEP and younger controls showed overlapping values, suggesting that these alterations may not be present at the onset and are not simply age-related.

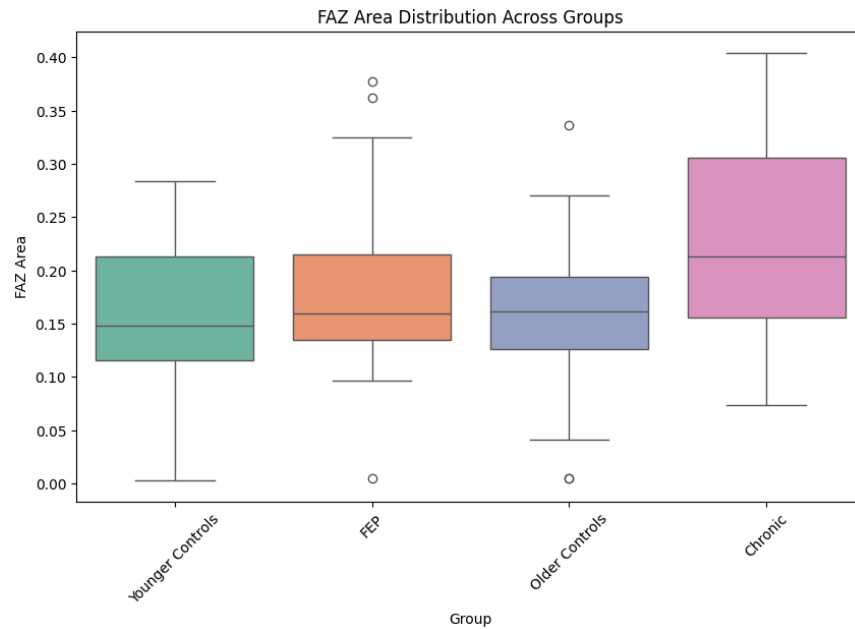


Figure 3.2 FAZ area distribution across the four groups

Normality was confirmed using the Shapiro-Wilk test, enabling the use of parametric statistics. Independent-samples t-tests showed no significant differences between younger controls and FEP, nor between FEP and chronic schizophrenia, but revealed a notable increase in FAZ area in chronic patients compared to older controls. Multi-group comparisons (ANOVA and Kruskal-Wallis) further validated that FAZ values differ significantly across classes. Effect size analysis (Cohen's d) indicated a large effect between older controls and chronic schizophrenia, strengthening the evidence that FAZ enlargement is clinically meaningful in advanced stages.

These results suggest that FAZ enlargement may reflect progressive neurovascular alterations associated with schizophrenia rather than serving as an early diagnostic marker. Because FAZ enlargement also occurs in several other neurological conditions, it should not be used in isolation; instead, it may contribute to a broader multimodal framework combining retinal, EEG, and neuroimaging markers. Future work should validate these findings in larger cohorts, assess the influence of medication, and explore AI-based fusion models to enhance diagnostic specificity.

Chapter 4

Remote healthcare monitoring of psychiatric patients

The integration of AI diagnostics and remote healthcare technologies has opened new possibilities for early detection and management of neurological and psychiatric conditions like schizophrenia. While retinal biomarkers such as FAZ area show promise, they may not be sufficient alone, highlighting the value of combining them with other data sources like EEG for a more reliable diagnosis.

AI-powered remote monitoring systems (wearables, IoT platforms, and ML models) enable continuous patient observation and can significantly enhance symptom tracking, treatment evaluation, and early detection of relapses in schizophrenia care.

4.1 Foundations of AI-Driven Remote Healthcare

The development of remote healthcare solutions has changed the landscape of medical care. It has shifted from traditional, face-to-face consultations to continuous monitoring with the use of IoT and AI. The integration of wearable devices, cloud computing, and AI algorithms allows clinicians to provide real-time, personalized care from a distance. These advancements have proved to have an impact in terms of diagnostic precision, timely therapeutic interventions, and long-term monitoring.

4.1.1 Short history in the development of remote healthcare

Remote healthcare originated as telemedicine in the mid-20th century, aiming to deliver medical services to underserved areas. While early systems relied on basic audio and video links, their effectiveness was limited by poor data transmission. With the rise of high-speed internet, mobile networks, and 5G, telemedicine has evolved into a real-time, scalable solution. The introduction of electronic health records (EHRs), cloud-based platforms, and mobile health (mHealth) technologies, including smartphones and wearables, has further expanded remote care by enabling continuous health monitoring and improving chronic disease management.

4.1.2 The role of IoT and AI in remote healthcare solutions

Continuous physical data and AI-powered EEG analysis can signal early alterations in neural activity associated with schizophrenia. These tools can open new opportunities for extending mental healthcare support into patients' homes, helping them stay engaged in their care through personalized and proactive strategies.

4.1.3 Advancements in Cloud Computing for IoT and AI-powered healthcare solutions

Cloud computing plays a key role in remote healthcare by enabling the secure storage and rapid access of EHRs, which improves decision-making and diagnostics in telemedicine. It offers important benefits such as scalability, useful during health crises, strong data security and General Data Protection Regulation (GDPR) compliance, and interoperability with IoT devices, apps, and wearables to support a more integrated view of patient health.

4.1.4 Current state of remote monitoring for neurological and psychiatric disorders

The integration of AI and remote monitoring technologies is transforming mental healthcare, particularly in managing complex disorders like schizophrenia. Traditional mental health systems face limitations such as poor accessibility, lack of real-time monitoring, and high resource demands. Advances in wearable devices, IoT, and AI are addressing these issues by enabling continuous, personalized care and early detection of symptoms. For schizophrenia, EEG-based AI models, especially DL approaches such as CNNs, Bi-LSTMs, and hybrid architectures, are showing high accuracy in diagnosis and monitoring. These innovations can empower patients to manage their conditions more independently and as these tools evolve, they promise a shift towards more proactive, scalable, and precise mental health care.

4.2 Case studies of AI in remote healthcare monitoring for schizophrenia patients

4.2.1 AI-driven monitoring of diet, physical health, and metabolism in schizophrenia patients

Schizophrenia is often accompanied by serious physical health complications such as obesity, diabetes, cardiovascular issues, and poor dietary habits. Emerging AI-enabled remote healthcare systems aim to fill this gap by providing continuous monitoring of diet, sleep, stress, and metabolic indicators through wearable devices. These tools allow for real-time tracking and personalized interventions, offering a more proactive approach to both physical and mental health management. For instance, integrating

physiological metrics like heart rate variability and glucose levels with behavioral data can reveal early signs of cognitive decline or symptom exacerbation. AI-driven decision support can then offer tailored nutritional guidance and automated alerts, helping to mitigate risks such as metabolic syndrome and support long-term wellness.

A key use case for personalized schizophrenia care is illustrated in Figure 4.1, showcasing a ML pipeline that processes data from diet, sleep, medication, and activity to deliver early warnings and personalized treatment recommendations. This system enables dynamic feedback and adaptation to individual needs and it also empowers patients through real-time insights into how their lifestyle choices impact mental health. By leveraging predictive analytics and continuous learning, such platforms move beyond reactive treatment models and pave the way for precision psychiatry. Integrating dietary monitoring, sleep tracking, and stress management within AI-based remote healthcare systems has the potential to reshape how schizophrenia is managed, making care more accessible, adaptive, and effective.

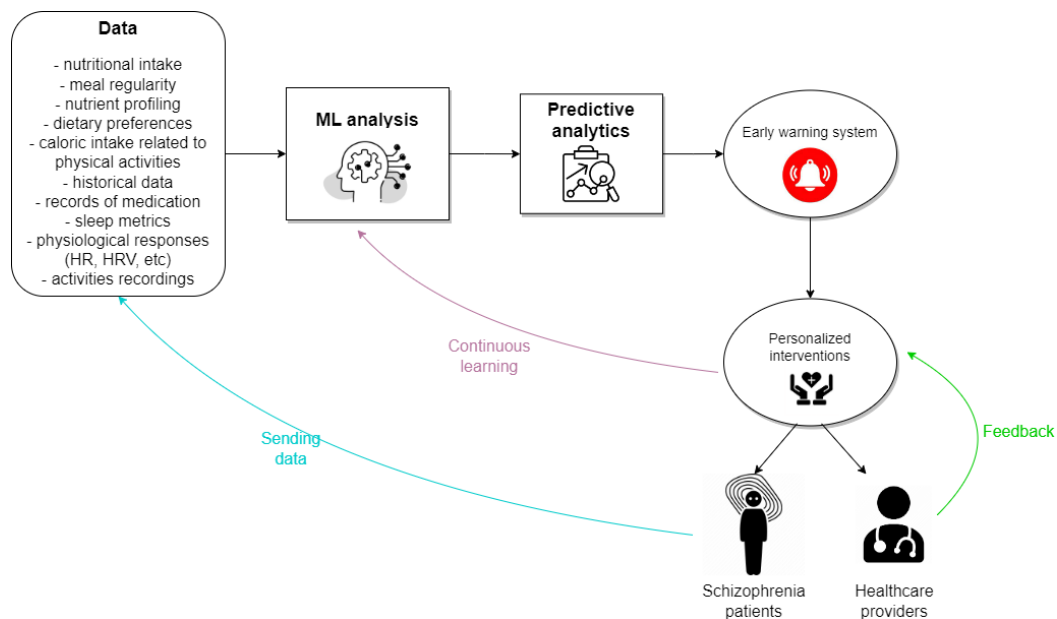


Figure 4.1 The use case flow for an application of personalized approach towards the patients with schizophrenia using ML

4.2.2 AI-powered EEG-based schizophrenia detection and monitoring

Alterations in brain connectivity, impaired neural processing, or irregular sensory-motor integration can significantly impact the evolution of schizophrenia. In this case, an important asset that can be used for diagnosis as well as for tracking disease progression is represented by EEG-based neuro-monitoring. EEG is a non-invasive, cost-effective technique that records brain electrical activity with high temporal resolution, enabling the analysis of neural oscillations, connectivity patterns, and event-related potentials (ERPs). All of them are altered in schizophrenia. EEG is used for understanding cognitive dysfunction, sensory abnormalities, and connectivity alterations in schizophrenia patients.

4.2.2.1 EEG dataset used for schizophrenia detection

This research utilized an open-source EEG dataset centered on schizophrenia, featuring recordings from 81 participants (49 diagnosed with schizophrenia and 32 HC). The experimental task involved three conditions to explore corollary discharge dysfunction: pressing a button to produce a sound (self-generated stimulus), hearing the sound passively (externally generated), and pressing a button without sound (motor-only control). This design aimed to detect sensory prediction abnormalities potentially linked to schizophrenia. The EEG data underwent several pre-processing steps to enhance signal clarity. These included re-referencing to earlobe electrodes, applying a 0.1 Hz high-pass filter to eliminate low-frequency noise, and interpolating missing data. After segmentation based on stimulus events, artifacts were removed, and ERP averages were extracted from nine key electrodes (Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, CP4) shown in Figure 4.3. The final dataset was normalized and prepared for further analysis, with class distribution visualized in Figure 4.2.

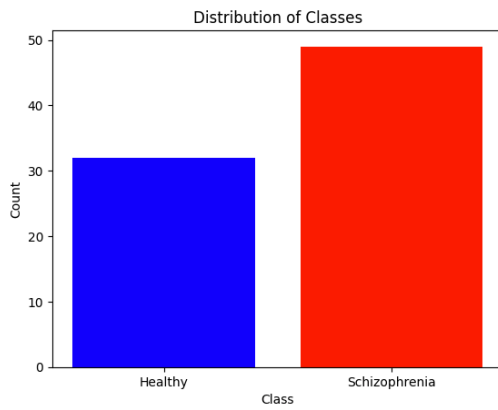


Figure 4.2 The distribution of classes in the dataset (left: control; right: schizophrenia)

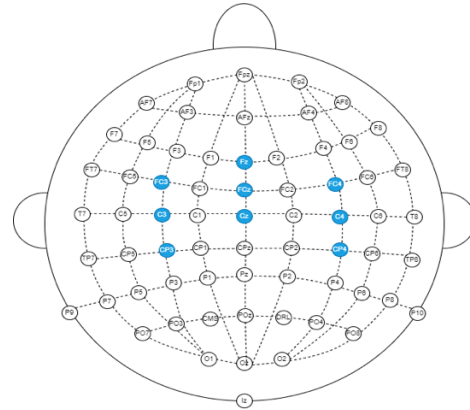


Figure 4.3 International 10-20 system for EEG electrodes on the scalp

4.2.2.2 1D-CNN, LSTM and CNN-LSTM DL models for schizophrenia classification

One developed study during this research was published in 2023 and it encompasses the description and applicability of three DL models: **(1) 1D-CNN model** which processes one-dimensional data using convolutional operations to gather local patterns and relationships between adjacent points, considered a natural fit for EEG data, which often contains these localized features; **(2) LSTM-based model** helps in capturing long-term dependencies in the EEG by effectively addressing the vanishing gradient problem; **(3) CNN-LSTM-based hybrid model** which allows for the simultaneous capture of short-term details and long-term trends. The training processes involve experimenting with multiple layers to achieve optimal model performance.

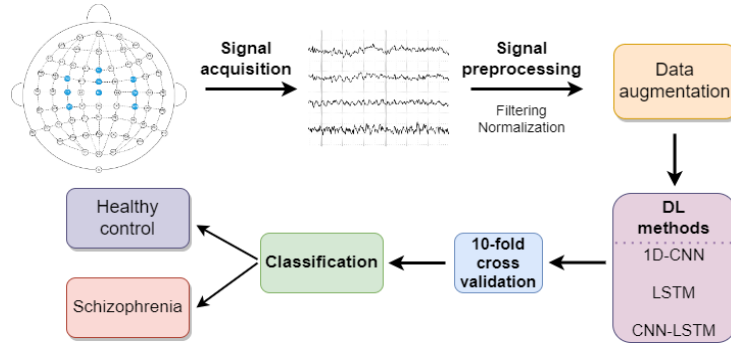


Figure 4.4 The diagram of the proposed method for EEG classification

Figure 4.4 presents a diagram that outlines the complete workflow for classifying EEG recordings into “Healthy Control” and “Schizophrenia”. The process begins with essential preprocessing steps: normalization, which standardizes the EEG data by removing scale differences, and filtering, which diminishes noise and unwanted artifacts, thus clarifying the signal. To enhance the dataset, data augmentation techniques such as noise injection are applied. The DL models are then trained and evaluated using a 10-fold cross-validation method which helps in assessing the model’s performance and generalizability.

The highest performance was observed with the CNN-LSTM model, which reached a test accuracy of 82%. The competitive results achieved by the LSTM and CNN-LSTM architectures highlight their ability to model the complex spectral and temporal characteristics present in EEG data. Additionally, employing a 10-fold cross-validation approach has contributed to the overall robustness of the classification models.

Table 4.1 The results for the proposed DL models

DL models	Time (s)	Results	
		<i>Accuracy</i>	<i>Loss</i>
1D-CNN	300	78.8%	0.56
LSTM	600	79.8%	0.63
CNN-LSTM	800	82.1%	0.45

4.2.2.3 CNN-BiLSTM model using TE Matrices

A significant advancement in this research was published in 2024 and the model was trained on Transfer Entropy (TE) matrices derived from EEG data, aiming to support schizophrenia diagnosis and prediction. Using the open-source dataset detailed in section 4.2.2.1, EEG signals from nine electrode sites (Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, CP4) were processed to compute TE matrices (quantitative indicators of directional brain connectivity, capturing how activity in one brain region influences another).

These TE matrices, visualized as asymmetric heatmaps, were input into a hybrid CNN-BiLSTM model. The CNN component extracted spatial features from the matrices, while the BiLSTM layer captured temporal dependencies, allowing the model to better detect subtle neural dysfunctions associated with schizophrenia. The matrices

were computed using 5-second EEG time windows and showed notably reduced connectivity in schizophrenia patients, especially in frontal and central regions (e.g., Fz, FCz, C3, C4), consistent with known impairments in cognitive and emotional regulation in the disorder (Figure 4.6a).

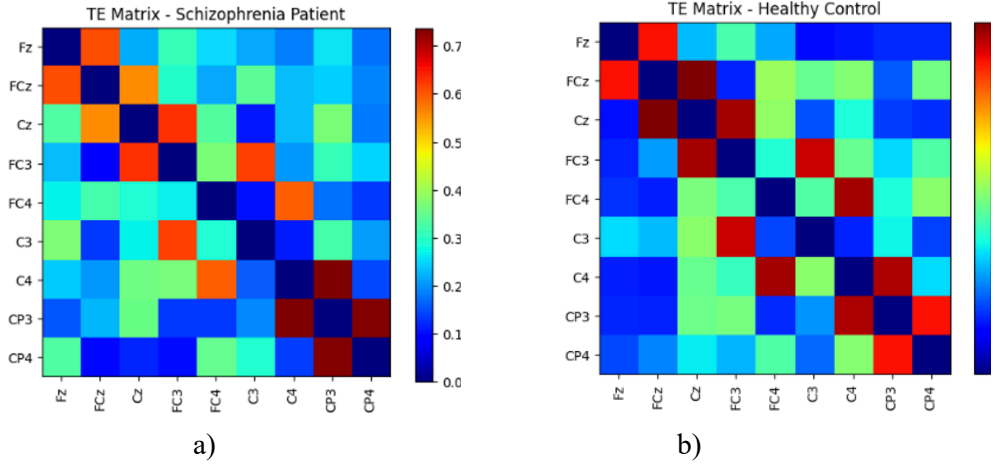


Figure 4.5 Directional connectivity heatmaps derived from TE values (unitless) are shown for (a) schizophrenia patients and (b) HC.

Figure 4.6 (b) presents the TE matrix for a HC, revealing enhanced connectivity with higher TE values, between central and parietal regions. This indicates a strong directional flow of information consistent with normal cognitive operations, which stands in contrast to the disrupted connectivity patterns seen in schizophrenia patients.

The CNN-BiLSTM model was trained using TE matrices derived from EEG data. This hybrid architecture extracts both spatial and temporal features, enabling precise classification between schizophrenia patients and HC. The model achieved an accuracy of 99.94%, demonstrating robust generalization and predictive performance. This outstanding convergence is reflected in the training and validation accuracy plots (Figure 4.7 a) and the loss curves (Figure 4.7 b).

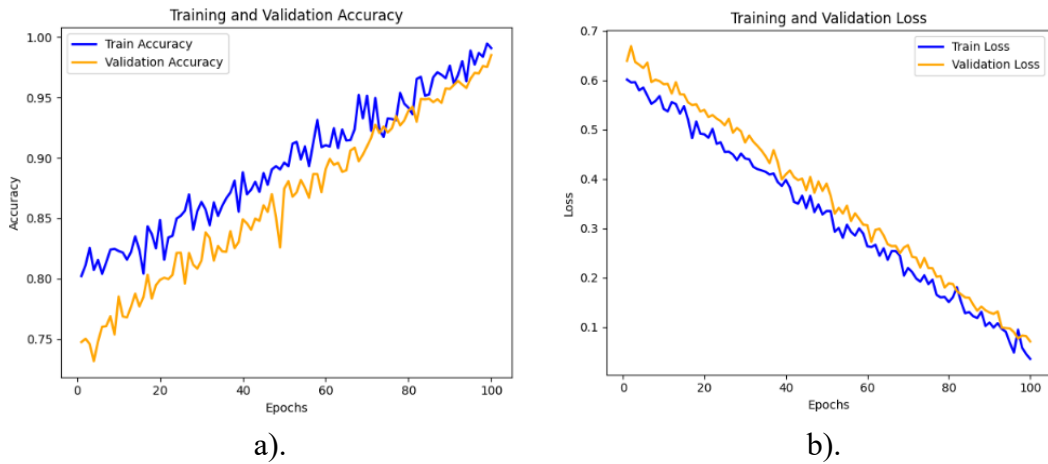


Figure 4.6 The plots for training and validation accuracy (a) and loss (b).

Figure 4.9 provides a visual representation of a proposed integration of the DL model into a remote health monitoring framework. The process begins with the acquisition of EEG signals from multiple electrodes. They are further processed to

generate TE matrices that capture neural connectivity patterns. These matrices are analyzed using a hybrid CNN-BiLSTM model that effectively captures the spatial and temporal characteristics of the EEG data.

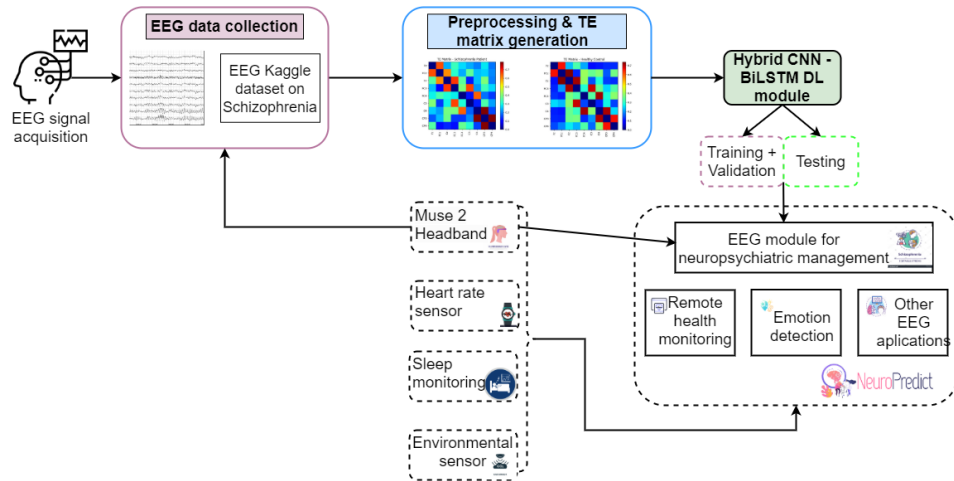


Figure 4.7 A conceptual model of how DL models can be integrated into a remote healthcare monitoring system

Table 4.2 Comparison with other AI-based techniques for schizophrenia detection using EEG data

Method	Technique	Accuracy	Study
SchizoGoogLeNet	CNN with GoogLeNet architecture	99.02%	Siuly et al.
Recurrence Plot + Gramian Angular Field	CNN-based spatial representations	93.2%	Ko and Yang
CNN-based EEG model	CNN for non-linear EEG signal classification	92%	Guo et al.
MSST-Bi-CNN	Multi-Scale Spectral Transformation with BiLSTM-CNN	84.42%	Jindal et al.
SchizoNET	Time-frequency analysis with CNN	99.74%	Khare et al.
1D-CNN	1D-CNN	78.8%	Present Research
LSTM	LSTM	79.8%	Present Research
CNN-LSTM	CNN-LSTM	82.1%	Present Research
Proposed CNN-BiLSTM (TE matrices)	CNN-BiLSTM on transfer entropy matrices	99.94%	Present Research

The proposed CNN-BiLSTM model achieved performance levels comparable to SOTA architectures such as SchizoGoogLeNet and SchizoNET. This research emphasized the applicability of TE matrices as they capture spatial and temporal patterns of neural

connectivity. The performance of the CNN-BiLSTM model can open up substantial opportunities for the integration into a comprehensive mental health monitoring system. This conceptual model of a remote health monitoring system, designed to collect EEG data with additional physiological and behavioral metrics, could provide real-time evaluations of neural connectivity patterns. These assessments are critical for the early detection of schizophrenia relapse or cognitive decline.

Moreover, there is a promising potential for real-time connectivity monitoring in clinical and remote environments as these models can be integrated into a remote healthcare monitoring system to be used in association with an EEG band that can be utilized at home or at distance.

Chapter 5

Conclusions

In concluding this doctoral journey, a road into neuro-ophthalmology health was explored, beginning in the microscopic details of retinal imaging, progressing through the delicate neural connections of the retina to the broader landscape of neurological and psychiatric disorders, culminating in the innovative domain of remote healthcare monitoring powered by AI.

The story started with the intricate dance between CNNs and ViTs, each with its own advantages at interpreting the subtle complexities within retinal OCT images. Hybrid models, such as ResNet50-ViT and FusionViT, were also effectively applied for disease diagnosis.

As the road went deeper, the retina's role evolved from being only the organ of sight to a window into neurological and psychiatric state. Through detailed analysis, fine retinal microvascular changes, such as FAZ enlargement, have been observed as progressive neurovascular dysfunctions in the progression of schizophrenia. These findings underscored the retina's potential to be a non-invasive biomarker.

Lastly, the road also ventured into the transformative landscape of remote healthcare monitoring. Using advanced AI models integrating CNNs and LSTM architectures, performant diagnostic accuracy for EEG monitoring were demonstrated.

The journey outlined in this thesis symbolizes a significant transformation in medical practice: one focused towards predictive, personalized, and remote healthcare empowered by AI. While the chapters have drawn to a close, the story of innovation and exploration continues.

5.1 Obtained results

The second chapter underlined the importance of retinal disease detection based on CNNs, ViTs and their hybrid versions. The experiments comparing CNNs, ViTs, and hybrid approaches for retinal disease classification using OCT images revealed several important aspects. The accuracy results for the CNN-based architectures are the following: DenseNet121 - 95.56%, DenseNet169 - 97%, DenseNet201 - 96%, InceptionResNet-V2 - 93.18%, and the 12 layers-based CNN with an accuracy of 93%. ViT and its extended version, DeepViT, used self-attention to comprehend the overall image context. They proved to be resource-intensive and demand large amounts of data,

but they provided state-of-the-art accuracies: ViT - 96.80% and DeepViT - 89.98%. Among the hybrid approaches that were used, the ResNet50-ViT and FusionViT models offered a promising compromise. The ResNet50-ViT model achieved the highest accuracy (99.97%), but its demand for computation load may limit its use in environments with limited resources. In comparison, FusionViT provided competitive accuracy (97.83%) with a considerably lower computational cost. This can make it more practical for real-time clinical applications.

The third chapter explored the role of FAZ area measurements in schizophrenia detection, revealing that FAZ enlargement is more pronounced in chronic schizophrenia patients than in early-stage cases. These findings align with the idea that vascular alterations in schizophrenia are progressive and may not be specifically present at the onset of the disorder. There were some statistical approaches that have been proposed in this chapter in order to validate the statement of FAZ enlargement correlated with schizophrenia. The value of 0.8868 for Cohen's d in the comparison between older controls vs. chronic schizophrenia indicates a large effect size. This validated that FAZ area enlargement in schizophrenia is not just statistically significant, but it can also be a clinically relevant one.

The fourth chapter highlighted the potential of advanced DL techniques that combined the strengths of CNNs and LSTM architectures for EEG data. The integration of TE-based features with the CNN-BiLSTM model further enhances the system's performance. It achieved a validation accuracy of 99.94% and it demonstrated the feasibility of real-time monitoring through wearable EEG devices. There was also a promising potential proved for real-time connectivity monitoring in clinical and remote environments as these models can be integrated into a remote healthcare monitoring system to be used in association with an EEG band that can be utilized at home or at distance. This chapter also integrated the relation between dietary habits and schizophrenia which highlighted a complementary path for personalized mental healthcare. Continuous dietary monitoring and metabolic health tracking can be integrated into remote healthcare systems in order to gain more insights into how nutritional patterns impact cognitive and emotional functioning in schizophrenia.

5.2 Original contributions

The primary contributions of this doctoral thesis include:

- (1) The development and evaluation of customized DL algorithms, including hybrid DL models, such as ResNet50-ViT and the creation of FusionViT architecture, specifically optimized for OCT-based retinal disease detection. FusionViT aimed at balancing computational efficiency with high diagnostic accuracy;
- (2) Introduction of a small size OCTA dataset and the comprehensive analysis and validation of retinal imaging biomarkers, with FAZ area measurements in particular. FAZ areas were proved to be non-invasive indicators for schizophrenia progression, which provided interesting insights into the disease's neurovascular aspects;

(3) Implementation and rigorous testing of advanced AI-driven remote healthcare monitoring systems, integrating EEG data and dietary monitoring. This led to a proposed conceptual model for a personalized approach to schizophrenia management. The development of CNN-BiLSTM model based on TE matrices generated from the EEG data is another original contribution to this thesis.

These contributions collectively enhance diagnostic practices and patient care across ophthalmology, neurology, and psychiatry.

5.3 List of original publications

This list includes only published / communicated papers in which the doctoral student is the author or co-author. To these are added the research reports from the doctoral program and the contracts on which the doctoral student worked. All these works can also be found in the Bibliography. All the mentioned works must have a content related to the topic of the doctoral thesis:

The following publications have a strong focus related to the subjects of the thesis:

1. **Elena-Anca Paraschiv**, Lidia Băjenaru, Cristian Petrache, Ovidiu Bica, and Dragoș-Nicolae Nicolau. 2024. "AI-Driven Neuro-Monitoring: Advancing Schizophrenia Detection and Management Through Deep Learning and EEG Analysis" *Future Internet* 16, no. 11: 424. <https://doi.org/10.3390/fi16110424>. WOS:001365026100001.
2. **Elena-Anca Paraschiv**, Marilena Ianculescu, Adriana Alexandru (2024). Bridging the Gap: Deep Learning EEG-Based Applications for Schizophrenia Classification and Management. In: Costin, HN., Magjarević, R., Petroiu, G.G. (eds) *Advances in Digital Health and Medical Bioengineering*. EHB 2023. IFMBE Proceedings, vol 109. Springer, Cham. https://doi.org/10.1007/978-3-031-62502-2_76. WOS:001326807700076.
3. **Elena-Anca Paraschiv**, Alina-Elena Sultana, "Harnessing the power of vision transformers for enhanced OCT image classification", *Romanian Journal of Information Technology and Automatic Control*, ISSN 1220-1758, vol. 34(2), pp. 97-111, 2024. <https://doi.org/10.33436/v34i2y202408>. WOS:001253386000008.
4. Laura-Ioana Coman, Marilena Ianculescu, **Elena-Anca Paraschiv**, Adriana Alexandru, and Ioana-Anca Bădăraș. 2024. "Smart Solutions for Diet-Related Disease Management: Connected Care, Remote Health Monitoring Systems, and Integrated Insights for Advanced Evaluation", *Applied Sciences* 14, no. 6: 2351. <https://doi.org/10.3390/app14062351>. WOS:001191807000001.
5. **Elena-Anca Paraschiv**, "Applications of Deep Learning algorithms for retinal diseases diagnosis based on Optical Coherence Tomography imaging," 2023 24th International Conference on Control Systems and Computer Science (CSCS), Bucharest, Romania, 2023, pp. 594-597, doi: 10.1109/CSCS59211.2023.00099.

6. Marilena Ianculescu, **Elena-Anca Paraschiv**, Adriana Alexandru, “The Potential of the Remote Monitoring Digital Solutions to Sustain the Mental and Emotional Health of the Elderly during and Post COVID-19 Crisis in Romania”, Healthcare 11, no. 4: 608. 2023. <https://doi.org/10.3390/healthcare11040608>. WOS:000939108500001.
7. **Elena-Anca Paraschiv**, Marilena Ianculescu, Ovidiu Bica and Alexandru Sipică, “Underpinning Improved Outcomes through Preventative Patient Care Models Based on Remote Monitoring and AI,” 2021 International Conference on e-Health and Bioengineering (EHB), Iasi, Romania, 2021, pp. 1-4, doi: 10.1109/EHB52898.2021.9657668. WOS:000802227900128.

The following publications are correlated with the subjects of the thesis:

1. Marilena Ianculescu, Victor Constantin, **Elena-Anca Paraschiv**, and Adriana Alexandru, “Design and Development of Comprehensive Health Tracking Devices for Enhanced Health Monitoring,” 2024 E-Health and Bioengineering Conference (EHB), IASI, Romania, 2024, pp. 1-4, doi: 10.1109/EHB64556.2024.10805642. WOS:001413708800046.
2. **Elena-Anca Paraschiv**, Marilena Ianculescu, Andreea Gusatu, Victor Constantin (2024) “Digital Health Platforms as Educational Tools: Enhancing Self-Management for Patients with Mental Health Conditions”, ICERI2024 Proceedings, pp. 4338-4347.
3. Adriana Alexandru. Marilena Ianculescu, **Elena-Anca Paraschiv** (2024). “Harnessing the Capabilities of IoHT-Based Remote Monitoring Systems for Decision Making in Elderly Healthcare”. In: Balas, V.E., Dzemyda, G., Belciug, S., Kacprzyk, J. (eds) Decision Making and Decision Support in the Information Era. Studies in Systems, Decision and Control, vol 534. Springer, Cham. https://doi.org/10.1007/978-3-031-62158-1_10
4. **Elena-Anca Paraschiv**, Cristian-Mihail Petrache, Ovidiu Bica, Ana-Mihaela Vasilevschi, “Fall Detection System: Continuous in-Home Monitoring of Parkinson’s Patients”, Proceedings of The 10th Edition of IEEE International Conference on e-Health and Bioengineering (EHB 2022), 17-19 Nov. 2022, Iasi – WEBCONFERENCE – Romania 2022 E-Health and Bioengineering Conference (EHB).
5. **Elena-Anca Paraschiv**, Cristian-Mihail Petrache, and Ovidiu Bica, “On the continuous development of IoT in Big Data Era in the context of Remote Healthcare Monitoring & Artificial Intelligence,” 2022 14th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Ploiesti, Romania, 2022, pp. 1-6, doi: 10.1109/ECAI54874.2022.9847503.
6. Marilena Ianculescu, **Elena-Anca Paraschiv**, Adriana Alexandru, “Addressing Mild Cognitive Impairment and Boosting Wellness for the Elderly through Personalized Remote Monitoring”, Healthcare 10, no. 7: 1214. 2022. <https://doi.org/10.3390/healthcare10071214>. WOS:000832374800001
7. **Elena-Anca Paraschiv**, Eleonora Tudora, Eugenia Tîrziu and Adriana

- Alexandru, “IoT & Cloud Computing-based Remote Healthcare Monitoring System for an Elderly-Centered Care,” 2021 International Conference on e-Health and Bioengineering (EHB), Iasi, Romania, 2021, pp. 1-4, doi: 10.1109/EHB52898.2021.9657585. WOS:000802227900049
8. Silvia Ovreiu, **Elena-Anca Paraschiv**, Elena Ovreiu, “Deep Learning & Digital Fundus Images: Glaucoma Detection using DenseNet”, ECAI 2021 13th Edition International Conference on Electronics, Computers and Artificial Intelligence, Pitesti, Romania, 2021, pp. 1-4, doi: 10.1109/ECAI52376.2021.9515188.

5.4 Perspectives for further developments

Future research should prioritize the refinement of multi-modal AI approaches, especially for schizophrenia detection and management, combining retinal imaging biomarkers with EEG and neuroimaging data. Developing advanced integration algorithms that seamlessly interpret multi-source data streams could significantly enhance early diagnosis accuracy and enable real-time monitoring of psychiatric and neurological conditions. Additionally, exploring efficient transformer architectures and optimized hybrid models could address current limitations related to computational resources, facilitating broader accessibility and adoption in diverse healthcare settings.

Moreover, advancements in wearable technologies and IoT-based healthcare platforms should continue to be explored to enhance remote patient monitoring capabilities further. Integrating continuous metabolic and dietary tracking into remote monitoring systems offers promising avenues for personalized interventions and holistic patient care. These integrative strategies have the potential to transform healthcare delivery profoundly, creating dynamic, adaptive, and responsive models that cater specifically to individual patient needs, ultimately improving healthcare outcomes and patient quality of life.

Bibliography

- David Turbert, “What Is Optical Coherence Tomography?,” American Academy of Ophthalmology.
- “Webvision - The organization of the retina and visual system,” Helga Kolb, Ralph Nelson, Eduardo Fernandez, Bryan Jones.
- M. O. F. A. Paul Chous, “Do diabetes, diabetic retinal disease contribute to macular degeneration?,” Optometry Times Journal.
- Y. Zhang, Z. Xing, and A. Deng, “Prediction of treatment outcome for branch retinal vein occlusion using convolutional neural network-based retinal fluorescein angiography,” *Sci Rep*, vol. 14, no. 1, p. 20018, Aug. 2024, doi: 10.1038/s41598-024-71061-7.
- T. H. M. Fung *et al.*, “Artificial intelligence using deep learning to predict the anatomical outcome of rhegmatogenous retinal detachment surgery: a pilot study,” *Graefe’s Archive for Clinical and Experimental Ophthalmology*, vol. 261, no. 3, pp. 715–721, Mar. 2023, doi: 10.1007/s00417-022-05884-3.
- T. Y. A. Liu, C. Ling, L. Hahn, C. K. Jones, C. J. Boon, and M. S. Singh, “Prediction of visual impairment in retinitis pigmentosa using deep learning and multimodal fundus images,” *British Journal of Ophthalmology*, vol. 107, no. 10, pp. 1484–1489, Oct. 2023, doi: 10.1136/bjo-2021-320897.
- R. Rashid, W. Aslam, A. Mehmood, D. L. R. Vargas, I. D. L. T. Diez, and I. Ashraf, “A Detectability Analysis of Retinitis Pigmentosa Using Novel SE-ResNet Based Deep Learning Model and Color Fundus Images,” *IEEE Access*, vol. 12, pp. 28297–28309, 2024, doi: 10.1109/ACCESS.2024.3367977.
- D. S. Kermany *et al.*, “Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning,” *Cell*, vol. 172, no. 5, pp. 1122–1131.e9, Feb. 2018, doi: 10.1016/j.cell.2018.02.010.
- K. Z. M. G. Daniel Kermany, “Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images,” *Mendeley Data*, V3, doi: 10.17632/rschjbr9sj.3, 2018.
- S. Ovreiu, E. A. Paraschiv, and E. Ovreiu, “Deep Learning Digital Fundus Images: Glaucoma Detection using DenseNet,” *Proceedings of the 13th International Conference on Electronics, Computers and Artificial Intelligence, ECAI 2021*, Jul. 2021, doi: 10.1109/ECAI52376.2021.9515188.
- Dosovitskiy, Alexey, et al. An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale. arXiv:2010.11929, arXiv, 3 June 2021. arXiv.org, <https://doi.org/10.48550/arXiv.2010.11929>.”
- Y. Iturria-Medina *et al.*, “Early role of vascular dysregulation on late-onset Alzheimer’s disease based on multifactorial data-driven analysis,” *Nat Commun*, vol. 7, no. 1, p. 11934, Jun. 2016, doi: 10.1038/ncomms11934.
- J. M. Yoon *et al.*, “Enhancing foveal avascular zone analysis for Alzheimer’s diagnosis with AI segmentation and machine learning using multiple radiomic features,” *Sci Rep*, vol. 14, no. 1, p. 1841, Jan. 2024, doi: 10.1038/s41598-024-51612-8.
- N. Aslam *et al.*, “Multiple Sclerosis Diagnosis Using Machine Learning and Deep Learning: Challenges and Opportunities,” *Sensors*, vol. 22, no. 20, p. 7856, Oct. 2022, doi: 10.3390/s22207856.
- A. Montolío, J. Cegoñino, E. Orduna, B. Sebastian, E. Garcia-Martin, and A. Pérez del Palomar, “A mathematical model to predict the evolution of retinal nerve fiber layer thinning

in multiple sclerosis patients,” *Comput Biol Med*, vol. 111, p. 103357, Aug. 2019, doi: 10.1016/j.combiomed.2019.103357.

- M. Siger, M. Owidzka, M. Świderek-Matysiak, W. Omulecki, and M. Stasiółek, “Optical Coherence Tomography in the Differential Diagnosis of Patients with Multiple Sclerosis and Patients with MRI Nonspecific White Matter Lesions,” *Sensors*, vol. 21, no. 21, p. 7127, Oct. 2021, doi: 10.3390/s21217127.
- M. Lai *et al.*, “A machine learning approach for retinal images analysis as an objective screening method for children with autism spectrum disorder,” *EClinicalMedicine*, vol. 28, p. 100588, Nov. 2020, doi: 10.1016/j.eclinm.2020.100588.
- A. Appaji *et al.*, “Deep learning model using retinal vascular images for classifying schizophrenia,” *Schizophr Res*, vol. 241, pp. 238–243, Mar. 2022, doi: 10.1016/j.schres.2022.01.058.
- S. D’Alfonso, “AI in mental health,” *Curr Opin Psychol*, vol. 36, pp. 112–117, Dec. 2020, doi: 10.1016/j.copsyc.2020.04.005.
- S. Siuly, Y. Li, P. Wen, and O. F. Alcin, “SchizoGoogLeNet: The GoogLeNet-Based Deep Feature Extraction Design for Automatic Detection of Schizophrenia,” *Comput Intell Neurosci*, vol. 2022, pp. 1–13, Sep. 2022, doi: 10.1155/2022/1992596.
- D.-W. Ko and J.-J. Yang, “EEG-Based Schizophrenia Diagnosis through Time Series Image Conversion and Deep Learning,” *Electronics (Basel)*, vol. 11, no. 14, p. 2265, Jul. 2022, doi: 10.3390/electronics11142265.
- Z. Guo, L. Wu, Y. Li, and B. Li, “Deep neural network classification of EEG data in schizophrenia,” in *2021 IEEE 10th Data Driven Control and Learning Systems Conference (DDCLS)*, IEEE, May 2021, pp. 1322–1327. doi: 10.1109/DDCLS52934.2021.9455509.
- K. Jindal, R. Upadhyay, P. K. Padhy, and L. Longo, “Bi-LSTM-deep CNN for schizophrenia detection using MSST-spectral images of EEG signals,” in *Artificial Intelligence-Based Brain-Computer Interface*, Elsevier, 2022, pp. 145–162. doi: 10.1016/B978-0-323-91197-9.00011-4.
- S. K. Khare, V. Bajaj, and U. R. Acharya, “SchizoNET: a robust and accurate Margenau–Hill time-frequency distribution based deep neural network model for schizophrenia detection using EEG signals,” *Physiol Meas*, vol. 44, no. 3, p. 035005, Mar. 2023, doi: 10.1088/1361-6579/acbc06.
- Z. Yin, J. Li, Y. Zhang, A. Ren, K. M. Von Meneen, and L. Huang, “Functional brain network analysis of schizophrenic patients with positive and negative syndrome based on mutual information of EEG time series,” *Biomed Signal Process Control*, vol. 31, pp. 331–338, Jan. 2017, doi: 10.1016/j.bspc.2016.08.013.
- E.-A. Paraschiv, L. Băjenaru, C. Petrache, O. Bica, and D.-N. Nicolau, “AI-Driven Neuro-Monitoring: Advancing Schizophrenia Detection and Management Through Deep Learning and EEG Analysis,” *Future Internet*, vol. 16, no. 11, p. 424, Nov. 2024, doi: 10.3390/fi16110424.