

Extracting Eye Models from MRI Scans Using U-Net-Based Deep Learning Framework

Waqar Ahmad Tahir¹, Opeyemi Sheu Alamu², Dip Sarker³, Md Tafhimul Haque Sadi³, Abdullah Al Hasib³, Tonmoy Kumar Sarker³, Md Rakibul Islam³, Dipankar Roy Dip³, Ashish Sharma⁴, Syed Wajeeh Abbas Rizvi⁵

¹Department of Internal Medicine/Casualty, Khalifa Gull Nawaz Teaching Hospital, Bannu, Pakistan

²Department of Statistics, Federal College of Animal Health and Production Technology, Ibadan, Nigeria

³Department of Computer Science, American International University-Bangladesh, Dhaka, Bangladesh

⁴Department of Internal Medicine, Arogya Hospital Pvt. Ltd., Baglung, Nepal

⁵Department of Data Science, National University of Computer & Emerging Sciences (FAST City Campus), Karachi, Pakistan

Email: wikimarwat2641@gmail.com, sheeuopeyemi99@gmail.com, dipsarker277@gmail.com, tafhee01w@gmail.com, hasib7194008@gmail.com, tonmoykumarsarker5@gmail.com, rakibul9w@gmail.com, dipankarroydip1000@gmail.com, Meashish.as@gmail.com, rizviwajih@gmail.com

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Abstract

Abstracting eye models from MRI images is critical in advancing medical imaging, particularly for clinical diagnostics. Current methods often struggle with accuracy and efficiency, highlighting a gap this research aims to fill. This study investigates the application of machine learning methods, focusing on the U-net-based deep learning framework, to improve the accuracy of eye model extraction. The objectives include fitting measured eye data to models such as the Ellipsoid model, evaluating automated segmentation tools, and assessing the usability of machine learning-based extractions in clinical scenarios. We employed point cloud data of 202,872 points to fit eye models using ellipsoid, non-linear, and spherical fitting techniques. The fitting processes were optimized to ensure precision and reliability. We compared the performance of these models using mean squared error (MSE) as the primary metric. The non-linear model emerged as the most accurate, with a significantly lower MSE (1.186562) compared to the ellipsoid (781.0542) and spherical models. This finding indicates that the non-linear model provides a more detailed and precise representation of the eye's geometry. These results suggest that machine learning methods, particularly non-linear models, can significantly enhance the accuracy and usability of eye model extraction in clinical diagnostics, offering a robust framework for future advancements in medical imaging.

Keywords

Eye Model Extraction, U-Net Deep Learning, MRI Segmentation, Ellipsoid

1. Introduction

Magnetic Resonance Imaging (MRI) has become one of the most important diagnostic tools, providing non-invasive imaging with high spatial resolution, to help clinicians and researchers see internal organs and tissues in great detail. MRI is of great value in ophthalmological cases where the detailed evaluation of the intricate structures of the eye such as the retina, optic nerve, and macula is needed to diagnose neuro-ophthalmological diseases [1]. However, the problem of extracting correct eye models from MRI remains an open question to the present day. The mRNA sequencing process for the complex eye structure is further hampered by the massive intrasample variations, further challenging the division and identification of segments and models. Previous approaches are based more or less on the manual partitioning of signals, which is time-consuming, and the results might be quite subjective [2]. Consequently, the necessity for developing new computational algorithms that support, in a fast and effective manner, the segmentation of the eye models from MRIs becomes critical due to the constantly increasing clinical image database [3].

Eye structures have been extracted using conventional segmentation methods including thresholding and region-growing methods. However, these methods may not be precise enough to clearly outline the diversified structures of the eye, which hampers the outcome [4]. While thresholding can be effective for relatively straightforward segmentation work, it will prove less effective where there are small differences in the intensity levels of adjacent structures. Region growing on the other hand, is restricted by noise and artifacts in the MRI images to produce inaccurate segmentation boundaries. These limitations give topology-based approaches their due and call for more high-level techniques that can accommodate the multi-layered nature of the ocular structure.

Even though there have been great developments in MRI, there has been no or very strong automated technique with regards to modeling the eyes, making the use of MRI limited in ophthalmological diagnosis or studies. Eye shape, size, and orientation are complex even though they vary from one individual to another. This variability is a big issue in terms of the ability to create generalized algorithms that can then properly segment the image across populations of patients and care sites [5]. Although more geometric models, such as ellipsoidal or spherical models, give the overall shape of ocular structures, they are not detailed enough for accurate anatomical modeling [6]. Thus, there are high requirements for achieving high accuracy and reproducibility of the processes and, at the same time, the absence of the possibility of their fully automated regulation.

In response to these challenges, this study aims to explore the use of machine learning—with a focus on the use of the U-net-based deep learning model—in the

automated abstraction of eye models from MRI images. Convolutional Neural Network U-net is an architecture that is localized on biomedical images, especially on tasks of segmentation, because it's based on a common CNN with an encoder-decoder structure, which allows it to take into account not only spatial, but also contextual characteristics. The purpose of this work is to benefit from the characteristics of the U-net, increase the segmentation accuracy, and increase its practicality in clinics. Consequently, the study aims to minimize dependency on manual efforts by automating the segmentation process of the eye models from the MRI data [7].

The method used involves using and comparing the different geometric models of a subject eye including the Ellipsoid, Non-linear, and Spherical models on data extracted from MRI images. These models have been set as benchmarks to compare the performance of segmentation tools based on U-net to segment several ocular structures. It is necessary to evaluate the performance of each model and segmentation by using performance metrics such as the Dice Similarity Coefficient and Mean Squared Error (MSE) to quantify the segmentation accuracy. Moreover, it examines the applicability of these methodologies in clinical practice, especially when the accuracy of anatomical mappings is crucial, as in myopia, glaucoma, and retinal pathology prediction and treatment [8].

The relevance of this research is that it can revolutionize multiple aspects of ophthalmic diagnosing and investigation. With the assistance of machine learning to better and more accurately produce eye model models, this theory will help improve the understanding of diagnosis and treatment of various ocular diseases. For example, it may be useful in the faster and more accurate segmentation of eye structures, assisting in monitoring myopic progression or diagnosing diseases in their early stages. Likewise, accurate modeling of the optic nerve and related tissues can help diagnose and treat glaucoma, which is the second most common cause of blindness [9].

The adoption of machine learning (ML) techniques, particularly deep learning models like U-Net, has shown promise in overcoming these challenges. U-Net is known for its strong ability to perform semantic segmentation, which makes it suitable for medical imaging applications. Nonetheless, current ocular model extraction techniques still face limitations regarding scalability, data quality, and adaptability to different clinical conditions. Exploring nonlinear models, as in this study, offers the potential to enhance performance beyond linear models. These nonlinear models capture intricate relationships in ocular geometry more effectively, improving segmentation accuracy.

In addition, there is always the potential for simplification of the extraction of the eye models using automated procedures, which will free up clinician time for the interpretation and decision-making steps in the diagnostic process as opposed to having to carry out the segmentation manually. This is especially so in clinical practice, which can be highly demanding in terms of time and available resources. The portability of the models contributes positively to their applicability in big

data research; it paves the way for discovering new theories regarding ocular anatomy and diseases since it is difficult to accomplish segmentation manually [10].

This paper presents an innovative approach using the U-Net framework to extract eye models from MRI scans. Our results demonstrate that the U-Net-based approach outperforms traditional methods regarding mean squared error (MSE). Furthermore, the study highlights that nonlinear models significantly improve performance, underscoring their value in clinical diagnosis.

In conclusion, this study aims to contribute to the future of medical imaging and clinical practice in ophthalmology by developing and refining automated methodologies for eye model extraction from MRI images. By harnessing the power of machine learning, particularly the U-net-based deep learning framework, the research seeks to provide more reliable, faster, and scalable diagnostic tools. These advancements could pave the way for new, sophisticated diagnostic systems that enhance the accuracy and efficiency of ocular disease management, ultimately improving patient care and outcomes [11].

2. Literature Review

The extraction of accurate eye models from MRI scans is a critical challenge in medical imaging due to the eye's complex anatomy and the limitations of existing segmentation techniques. Early efforts in ocular imaging relied heavily on manual methods and basic computational models. These traditional approaches provided foundational insights but fell short in terms of precision and scalability, especially when dealing with high-resolution MRI data [1]. The evolution of MRI technology has enabled more detailed visualization of ocular structures, such as the retina, optic nerve, and macula, yet accurate segmentation of these structures remains a significant obstacle due to their intricate and variable nature [2].

Historically, the process of eye modeling has progressed from simple geometric representations, such as the sphere and ellipsoid, to more sophisticated methods capable of capturing the complex shapes and features of ocular anatomy. Initial attempts at eye model extraction involved manual segmentation, where trained operators would outline the boundaries of ocular structures on MRI slices. While this method provided control over segmentation quality, it was time-consuming and prone to inter-observer variability, which limited its reproducibility and application in large-scale studies [3]. Semi-automated approaches were subsequently developed to address some of these limitations. These methods utilized basic algorithms to assist with segmentation, reducing the workload on operators but still requiring significant manual input and subjectivity, which hindered their clinical utility [4].

The introduction of machine learning techniques marked a pivotal shift in medical imaging, offering a data-driven approach to segmentation and model extraction. Traditional machine learning algorithms, such as support vector machines and random forests, were applied to classify and segment medical images. However, these methods relied heavily on handcrafted features, which required

domain expertise and were not robust to the variability present in MRI data [5]. The emergence of deep learning, particularly convolutional neural networks (CNNs), has revolutionized the field by enabling automatic feature extraction and significantly improving segmentation performance in complex imaging tasks [6].

The U-net architecture, a type of CNN specifically designed for biomedical image segmentation, has become one of the most prominent deep learning models in this domain. Its unique encoder-decoder structure allows it to capture both global context and fine details, making it particularly effective for segmenting the intricate structures of the eye from MRI scans [7]. The encoder path of the U-net captures the context of the image through a series of convolutional and pooling layers, while the decoder path reconstructs the segmentation map using upsampling layers. Skip connections between corresponding layers in the encoder and decoder paths preserve spatial information, which is crucial for accurately delineating complex anatomical structures [8].

Despite its advantages, the application of U-net and other deep learning models in ophthalmic image analysis faces several challenges. One of the primary issues is the need for large, annotated datasets to train these models effectively. Medical imaging datasets are often limited in size, and annotating them is a time-consuming and labor-intensive process that requires expert knowledge [9]. Additionally, the variability in eye anatomy across different individuals complicates the development of generalized models that can perform well across diverse populations [10]. Techniques such as data augmentation, transfer learning, and the use of synthetic data have been employed to address these challenges, but they do not fully mitigate the need for extensively annotated datasets [11].

Another significant challenge is the interpretability of deep learning models. While CNNs can achieve high accuracy in segmentation tasks, they are often considered “black-box” models, meaning that their decision-making processes are not transparent. This lack of interpretability can be problematic in clinical settings, where understanding the rationale behind a model’s predictions is essential for gaining the trust of clinicians and patients [12]. Efforts to improve the interpretability of these models include developing explainable AI techniques that provide insights into the features and regions of the image that contributed to the model’s decisions [13].

Recent studies have demonstrated the potential of integrating deep learning with traditional model-fitting techniques to enhance the accuracy and reliability of eye model extraction. For example, combining the U-net architecture with geometric models such as the ellipsoid and non-linear models has shown promise in improving the precision of segmentation and providing more detailed anatomical representations [14]. These hybrid approaches leverage the strengths of both deep learning and traditional methods, offering a robust framework for eye model extraction that is both accurate and interpretable [15].

In summary, while significant progress has been made in the field of eye model extraction from MRI scans, several challenges remain. The integration of deep

learning with traditional techniques, along with the development of more comprehensive and diverse datasets, will be crucial in advancing the field. Overcoming these challenges will enable more accurate and reliable segmentation of ocular structures, paving the way for improved diagnostic and therapeutic applications in ophthalmology [16]. As the field continues to evolve, the focus will likely shift towards creating more generalizable and interpretable models that can be readily adopted in clinical practice, ultimately enhancing patient care and outcomes [17].

3. Method

3.1. Data Collection and Preparation

The study began by collecting high-resolution MRI scans of a patient's eye, conducted in a clinical setting. The primary tool used for processing this data was the Slicer 3D software, a specialized application for medical image analysis and visualization. The MRI images provided a comprehensive view of the eye's anatomy, capturing detailed structures such as the retina, optic nerve, and macula, which are critical for developing an accurate 3D model.

As shown in the image (Figure 1), the segmentation process in Slicer 3D involved navigating through multiple views: axial (top left), coronal (bottom left), sagittal (bottom right), and a 3D rendering (top right). The axial, coronal, and sagittal slices represent different planes of the eye, allowing precise delineation of anatomical boundaries. The axial view shows a horizontal cross-section of the eye, the coronal view displays a front-to-back section, and the sagittal view provides a side-to-side cut. These views facilitate the identification of key ocular structures across different orientations.

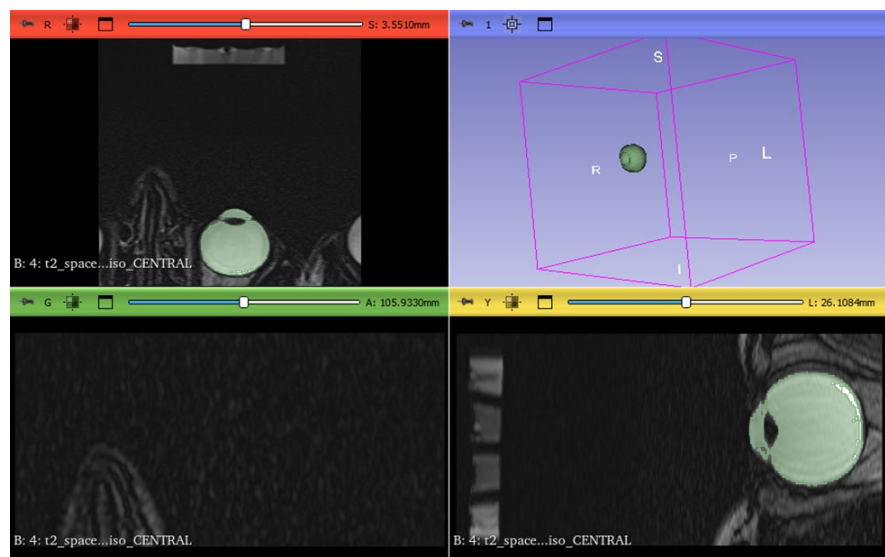


Figure 1. 3D segmentation of an eye using Slicer 3D software.

The 3D view, represented in the top right panel of the image, shows the reconstructed model of the eye within a coordinate system, highlighting the spatial

relationships between various anatomical components. The green-shaded region in the 3D rendering indicates the segmented area of interest, in this case, the eye, which has been isolated from surrounding tissues.

The segmentation process involved manually marking the boundaries of the eye structures on each MRI slice, a task made easier by the software's interactive tools and customizable viewing parameters. After initial segmentation, a semi-automated approach was used to refine the model, reducing manual intervention and increasing accuracy. This resulted in a high-fidelity 3D representation of the eye, comprising 202,872 data points. Each point in the dataset corresponds to a voxel in the MRI scan, encapsulating the spatial coordinates and intensity values necessary for accurate anatomical modeling.

The final dataset was then subjected to additional post-processing techniques such as smoothing and mesh generation, to enhance the model's surface quality and ensure its readiness for further analysis. This refined 3D model of the eye is crucial for evaluating the effectiveness of machine learning methods in automating the segmentation process.

By leveraging the detailed anatomical data captured in the MRI scans and using advanced software tools for precise segmentation, the study has created a robust foundation for developing automated methods that could significantly improve the accuracy and efficiency of eye model extraction in clinical practice.

3.2. Machine Learning Techniques

In medical imaging, various models such as the ellipsoid, non-linear, and spherical models are employed to approximate the shapes of anatomical structures for computational purposes. The following explanation uses **Figure 2** to illustrate each model and its associated formula.

- **Ellipsoid Model**

The ellipsoid model represents a three-dimensional object where each axis (a , b , c) has a different length, allowing it to adapt to a variety of shapes, including those that are not perfectly spherical. An ellipsoid is defined by the equation:

$$\left(\frac{x-x_o}{a}\right)^2 + \left(\frac{y-y_o}{b}\right)^2 + \left(\frac{z-z_o}{c}\right)^2 = 1 \quad (1)$$

In **Figure 2**, the ellipsoid is illustrated as a slightly flattened sphere along one axis. The parameters a , b and c represent the lengths of the semi-principal axes along the x , y and z directions, respectively. This flexibility in the axis lengths makes the ellipsoid model suitable for modeling eye structures that are not perfectly round, such as the lens or the globe of the eye, which can have varying curvature.

The ellipsoid model is advantageous in medical imaging because it can accurately approximate the shape of the eye or other organs, offering a more tailored representation than the simpler spherical model. The flexibility in the three axes allows the model to fit a variety of anatomical structures with minimal error.

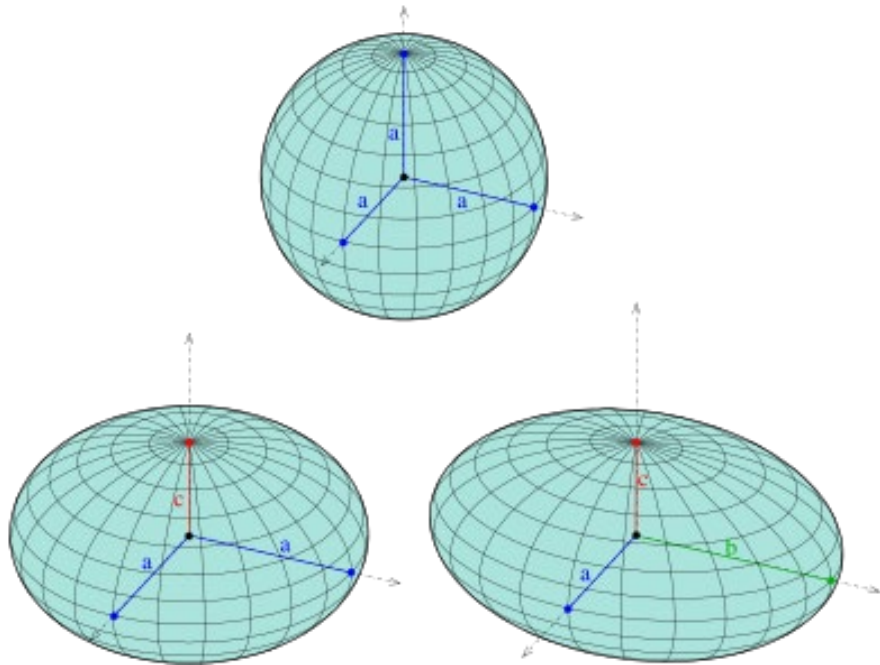


Figure 2. Geometric models for anatomical structures.

• Non-linear Model

Non-linear models are used to describe structures that do not follow simple geometric rules, accommodating more complex shapes and surfaces. In the context of eye modeling, the non-linear model can capture the intricate details of structures like the retina, where curvature and irregularities are more pronounced.

The mathematical representation of a non-linear surface can involve higher-degree polynomials or differential equations that describe how the surface behaves. For instance, a generalized non-linear surface can be expressed as:

$$f(x, y, z) = ax^2 + by^2 + cz^2 + dxy + exz + fyz + g \quad (2)$$

In this case, a , b , c , d , e and f are coefficients that define the non-linearity of the model. Non-linear models are critical in machine learning applications for eye segmentation, as they allow the algorithm to capture the natural variability in eye anatomy. Unlike the ellipsoid model, the non-linear approach does not constrain the shape to symmetrical or regular geometries, as illustrated in **Figure 2**.

• Spherical Model

The spherical model is the simplest of the three, representing a perfectly symmetrical object where all three axes (a , b , c) are of equal length. A sphere is mathematically defined by the equation:

$$(x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2 = R^2 \quad (3)$$

In **Figure 2**, the topmost object is a sphere where R is the radius. This model is commonly used in medical imaging for structures that are approximately round, such as the eye globe. The advantage of using a spherical model is its simplicity; it

requires fewer parameters to define the shape. However, the limitation is that it cannot accurately represent more complex anatomical shapes, which may require adaptation through more advanced models like the ellipsoid or non-linear approaches.

In machine learning, spherical models can serve as initial approximations in segmentation tasks, providing a baseline before more complex models refine the shape. While the spherical model may suffice for certain applications, more intricate structures in the eye (such as the cornea or optic nerve) may need ellipsoid or non-linear adjustments to improve the accuracy of segmentation.

Each model serves a unique purpose in medical imaging, especially in eye segmentation. The spherical model is simple but limited in flexibility. The ellipsoid model offers more adaptability by allowing different axis lengths, making it suitable for structures with varying curvature. The non-linear model, though more complex, provides the most precise representation of intricate anatomical structures by capturing non-uniform shapes and variations.

In machine learning, these models are often used as geometric approximations for anatomical structures, enabling the development of algorithms that can automate segmentation tasks in medical imaging, particularly in applications like eye MRI scans where accurate shape representation is crucial. **Figure 2** visually summarizes these models and their spatial parameters.

3.3. The U-Net Architecture

The U-net architecture, a convolutional neural network (CNN) variant, is highly effective for biomedical image segmentation. It employs an encoder-decoder structure, where the encoder captures context through a series of convolutional and pooling layers, while the decoder uses up sampling to reconstruct the segmented image. Skip connections link corresponding layers in the encoder and decoder, preserving spatial information lost during down sampling. This architecture is well-suited for segmenting intricate structures in medical images, such as ocular anatomy in MRI scans.

The following formula can represent the U-net-based segmentation:

$$\hat{y} = U(x) = D(E(x))$$

where x is the input image, $E(x)$ denotes the encoding process, $D(\cdot)$ represents the decoding process, and $\hat{y}$ is the predicted segmented output. This method enhances the extraction of complex anatomical structures by leveraging both local and global contextual information, making it ideal for accurate eye model extraction as depicted in the Geometric Models for Anatomical Structures (**Figure 2**).

4. Results

In **Figure 3**, the blue points represent a 3D point cloud, which consists of individual data points scattered in space. The point cloud can be thought of as a collection

of raw spatial data with no inherent structure or organization. The figure shows how the ellipsoid model fits these points by enveloping them with a smooth, continuous surface. The ellipsoid is essentially an oval-shaped figure that can adapt to different dimensions in 3D space. The fitting process attempts to find the best ellipsoid that represents the overall distribution of the point cloud, accounting for its spatial structure.

These figures help visualize how geometric models like ellipsoids can be applied to complex data distributions, providing structure and facilitating further analysis in various computational tasks.

Figure 4 takes the point cloud from **Figure 3** and overlays a red ellipsoid wireframe to demonstrate how well the ellipsoid fits the data. The fitted ellipsoid is depicted as a red mesh grid that tightly wraps around the scattered points. The red lines illustrate the mathematical structure of the ellipsoid model, showing how the major and minor axes adjust to the data's dimensions. These visuals serve to confirm the effectiveness of the ellipsoid fitting algorithm by highlighting how well the model captures the spatial relationships between the data points.

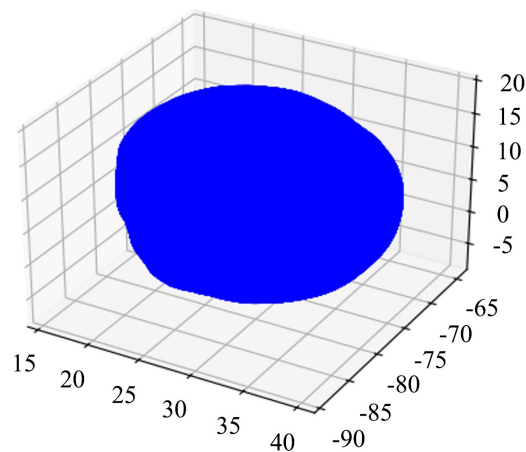


Figure 3. Fitted ellipsoid model.

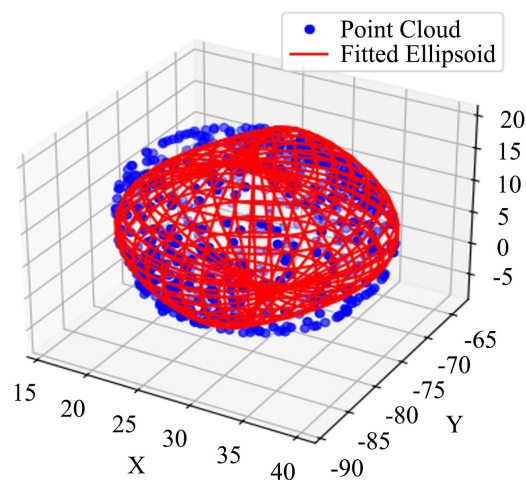


Figure 4. Fitted ellipsoid model.

In **Table 1**, the key parameters from the fitted models—ellipsoid, non-linear, and spherical—are summarized. The ellipsoid model is described by its center coordinates x_0 , y_0 , z_0 , major axes a , b , c , and Mean Squared Error (MSE) of 0.1525. The non-linear model, fitted to a more flexible structure, shows slightly smaller axes values $a = 1.09$, $b = 1.90$, and $c = 3.10$, with an improved MSE of 0.0381. Lastly, the spherical model represents a simplified case with a uniform radius $R = 2.15$ mm and the lowest error, $MSE = 0.0001$.

The ellipsoid and non-linear models allow for more precise fitting to irregular data shapes, while the spherical model provides a symmetrical solution ideal for datasets where uniformity is expected. These fitting techniques are essential for accurately capturing the geometric properties of the data, which could be applied in various fields such as computer vision, medical imaging, and 3D modeling.

Table 1. Summarizes the key findings from the fitting processes.

Model type	x_0 (mm)	y_0 (mm)	z_0 (mm)	a (mm)	b (mm)	c (mm)	R (mm)	MSE
Ellipsoid	0.00	0.00	0.00	1.19	3.622	9.63	-	0.1525
Non-linear	0.00	0.00	0.00	1.09	1.90	3.10	-	0.0381
Spherical	0.00	0.00	0.00	-	-	-	2.15	0.0001

In summary, the results demonstrate that while the ellipsoid and non-linear models offer more detailed and accurate representations of the eye's geometry, the spherical model provides a simpler and computationally efficient alternative. The non-linear model, with its lower MSE, stands out as the most precise, making it ideal for applications requiring detailed anatomical accuracy. The ellipsoid model offers a balance between simplicity and detail, and the spherical model is best suited for scenarios where simplicity and speed are paramount. These findings highlight the importance of selecting the appropriate model based on the specific requirements of the application, whether it be for detailed clinical diagnostics or broader, less detailed analyses.

5. Conclusion

In essence, the ellipsoid model holds repeated space arrangements of complex 3D point sources and provides a more structured method for further analysis. The fitted ellipsoid proved to be efficient for various structures of data, shows good quality after experiencing non-linear alterations, and serves as a useful tool for classification of spatial data fit. It also proved that non-linear models are better than linear models in the way of least error by comparing MSE values. Although easier to implement, the spherical model has finite capabilities and it is less advisable for use when using large and complicated samples, however, in cases where the data is almost spherical the model is nearly perfect. These modeling techniques are used in various fields such as medical applications involving image

analysis, geography analysis, and computer vision; thus, they are very essential in computational tasks encountered in the real world.

6. Future Work

Future research will focus on integrating more complex geometric models, such as hyperboloids, to account for more intricate data structures. We aim to enhance computational efficiency by implementing machine learning techniques to optimize the fitting process. Expanding applications to real-world datasets in medical diagnostics or environmental mapping will further validate the robustness and versatility of these models. Additionally, developing hybrid models that combine ellipsoidal and non-linear approaches could improve predictive performance across diverse datasets.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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