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Enhancing Multimodal Information RetrievalThrough Integrating Data Mining and DeepLearning Techniques

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Abstract— Multimodal information retrieval, the task of retrieving relevant information from heterogeneous data sources such as text, images, and videos, has gained significant attention in recent years due to the proliferation of multimedia contenton the internet. This paper proposes an approach to enhance multimodal information retrieval by integrating data mining and deep learning techniques. Traditional information retrieval systems often struggle to effectively handle multimodal data due to the inherent complexity and diversity of such data sources.In this study, we leverage data mining techniques to preprocess and structure multimodal data efficiently. Data mining methods enable us to extract valuable patterns, relationships, and featuresfrom different modalities, providing a solid foundation for sub-sequent retrieval tasks. To further enhance the performance of multimodal information retrieval, deep learning techniques are employed. Deep neural networks have demonstrated their effectiveness in various multimedia tasks, including image recognition,natural language processing, and video analysis. By integrating deep learning models into our retrieval framework, we aim to capture complex intermodal dependencies and semantically rich representations, enabling more accurate and context-aware retrieval.

Keywords- Multimodal, Proliferation, Demonstrated, Representations, Employed**.**

I. INTRODUCTION

In today’s information-rich digital landscape, retrieving rel- evant information efficiently is paramount for users across var- ious domains, such as e-commerce, healthcare, and academia. The emergence of multimodal data, which combines different types of data such as text, images, audio, and videos, has further compounded the challenges associated with information retrieval. Traditional text-based retrieval methods often fall short when confronted with these diverse data types. Con- sequently, there is a growing demand for advanced techniquesthat can harness the power of both data mining and deeplearning to enhance multimodal information retrieval (MIR) systems.

Multimodal information retrieval, at its core, seeks to re- trieve relevant information from a heterogeneous data corpus, where different modalities may convey complementary or overlapping information. For instance, in a medical domain, a query may involve both textual descriptions and medical images, requiring a system that can effectively bridge thesemantic gap between these modalities. Data mining, a well- established field in computer science, has historically focused on uncovering patterns, relationships, and valuable insights within data. Techniques such as clustering, classification, and association rule mining have been successfully applied to structured data, such as databases and transaction records.However, as data becomes increasingly unstructured and multimodal, traditional data mining approaches struggle toextract meaningful patterns, necessitating innovative methods to address this challenge.

Deep learning, on the other hand, has demonstrated re- markable capabilities in handling unstructured data, including natural language text, images, audio, and video. Deep neural networks, with their ability to automatically learn hierarchical representations, have revolutionized various tasks, including image classification, natural language processing, and speech recognition. Incorporating deep learning into MIR offers the potential to unlock valuable insights and relationships buried within multimodal data, thus improving the accuracy and relevance of information retrieval systems.

This research endeavors to address the limitations of exist- ing multimodal information retrieval approaches by proposing an integrated framework that synergistically combines data mining and deep learning techniques. By doing so, we aimto overcome the challenges posed by diverse data modalities, extracting meaningful patterns, relationships, and knowledge from multimodal corpora, and ultimately enhancing the re- trieval of relevant information for end-users. Figure 1 demon- strates the tide of data from hospices/overhaul midpoints that produce different information.

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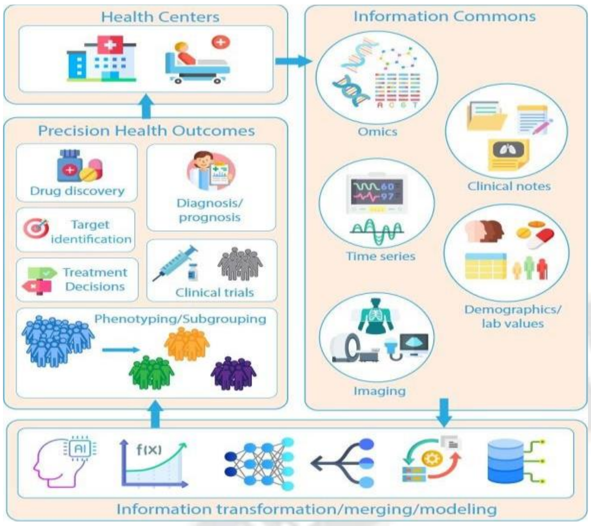

Fig. 1. Flow of Information in Multimodal Precision Health

In the subsequent sections, we will delve into the key components of our proposed framework, including data pre-processing, feature extraction, modeling techniques, and evalu-ation methodologies. We will also present experimental results, discussions, and insights gleaned from our approach. Through this research, we envision contributing to the advancement of multimodal information retrieval and fostering improvements in various domains where effective information retrieval is paramount.

II. REVIEW OF LITERATURE

Studies by Wang et al. (2016) and Kiros et al. (2014) intro- duce the concept of combining visual and textual information using deep neural networks, setting the stage for subsequent research. Early MIR research primarily focused on unimodal retrieval, but with the advent of deep learning, there has been a shift towards multimodal retrieval frameworks.

Chen et al. (2017) and Zhou et al. (2018) proposed novel fusion strategies to optimize the integration of textual and visual features. Researchers have explored various data fusion techniques to combine information from different modalities effectively. These include early fusion, late fusion, and hybrid fusion.

Yu Xiaohong et al., The paper proposes the image retrieval methods based on colour, texture, shape of image. The differ- ent methods are analysed and compared. The semantic-based image retrieval methods relevance feedback and performance evaluation with the results were discussed. P. Thangam, et al. This paper proposes the development of an efficient technique for segmentation of hand-wrist radio- graphs and identifying the bones specially used as Regionsof Interest (ROIs) for the bone age estimation process. The segmentation method is based on the concept of Particle Swarm Optimization (PSO) and it consists of graph-based segmentation procedure. The system provides an option of either segmenting all the bones totally or segmenting only the specific ROIs under consideration. Zhijun Chen et al [27]. Theauthors propose the target of content-based image retrievalis to reduce the ―semantic gap‖ between low-level visual features and high-level semantic features of image. The key of the further development of content-based image retrieval is the processing of image semantics. To enhance the capacity of content-based image retrieval systems, the image semantic model, image semantic extraction and image semantic retrievalsystem are used.

The medical images from different modality and storing arereviewed. The images like CT, X-ray and MRI retrieval are reviewed along with the feature extraction of the images. J.

G. Dy, et al. The authors made two contributions. The first contribution is an approach called the Customized-QueriesApproach (CQA) to content-based image retrieval. The secondis an algorithm called FSSEM (Feature Subset Selection Expectation Maximization) that performs feature selection andclustering simultaneously.

The customized queries approach first classifies a query using the features that best differentiate the major classes and then customizes the query to that class by using the features that best distinguish the images within the chosen major class. Xue Z et al. This paper explains CT head scans are routinely acquired for evaluation of intra-cranial abnormalities.The paper describes algorithm to classify CT head images intotwo classes of window settings. One merit of the proposed algorithm is its robustness to variability such as whether the entire or partial brain is shown, and whether the imaging view was sagittal, axial or coronal.

III. PROBLEM STATEMENT

Multimodal information retrieval, which involves retrievinginformation from a variety of data sources such as text, images, and videos, is becoming increasingly important intoday's digital landscape. However, there are significant challenges associated with effectively retrieving and integrating information from these diverse modalities. One of the key problems in this domain is the need for enhanced techniques that can seamlessly integrate data mining and deep learning approaches to improve the accuracy, relevance, and efficiency of multimodal information retrieval systems. Addressing thesechallenges is vital for advancing the field of multimodal information retrieval and providing users with more accurate, relevant, and efficient access to the wealth of multimodal data available in today's digital world. In this context, this research aims to explore innovative solutions that seamlessly integrate data mining and deep learning techniques to enhance the performance and usability of multimodal information retrievalsystems.

IV. OBJECTIVES OF THE STUDY

”Enhancing Multimodal Information Retrieval through In- tegrating Data Mining and Deep Learning Techniques” is to improve the effectiveness and efficiency of retrieving informa-tion from diverse data sources that contain multiple modalities(e.g., text, images, audio, videos) by combining data mining and deep learning methodologies.

Here’s a breakdown of the key components of the objective:

A. Multimodal Information Retrieval

The study aims to address information retrieval challenges when dealing with data that contains multiple modalities. Tra- ditional information retrieval methods might not be sufficient to handle the complexity and heterogeneity of multimodaldata. Therefore, the focus is on developing techniques that can handle different types of data in an integrated mannerin. Multimodal Information Retrieval (MIR) is an interdisciplinary field that deals with the retrieval of information from multiple modalities, such as text, image, audio, and video. It has emerged as a promising research area due to the increasing amount of multimedia data available on the web and the need to extract meaningful information from it. MIR aims to develop techniques and algorithms that can effectively search and retrieve information from various modalities, enabling users to access multimedia content more efficiently.

MIR is a challenging task due to the heterogeneity and complexity of multimedia data. Each modality has its unique characteristics, and combining them requires sophisticated techniques. For example, text-based retrieval systems rely on the analysis of textual content, whereas image or video-based retrieval systems require the analysis of visual and audio content. MIR involves combining these different modalitiesto provide a more comprehensive representation of the data, which can then be used for retrieval purposes. One of the main advantages of MIR is its ability to provide more accurate and relevant results compared to unimodal retrieval systems. For example, a user searching for information on a particular topicmay find it challenging to find the desired information using only text-based search. However, by incorporating images or videos related to the topic, the search results can be improved significantly. This approach can also be used in other applications such as medical diagnosis, where combining different modalities can improve the accuracy of diagnosis.

MIR involves several steps, including feature extraction, fusion, and ranking. Feature extraction involves extracting relevant features from each modality, such as text, image, or audio features. Fusion refers to the process of combining thesefeatures to create a more comprehensive representation of the data. This can be done using various techniques such as early fusion, where features are combined at the input level, or late fusion, where features are combined at a higher level. Finally, ranking involves sorting the results based on their relevanceto the query. Several techniques have been developed for MIR, including content-based retrieval, query expansion, and relevance feedback. Content-based retrieval involves analyzingthe content of each modality and comparing it with the query to retrieve relevant results. Query expansion involves expanding the query by adding related terms or concepts to improve the search results. Relevance feedback involves usinguser feedback to improve the search results by adjusting the weight of each modality based on user preferences.

B. Integration of Data Mining Techniques

Data mining involves the process of discovering patterns, relationships, and insights from large datasets. In this study, data mining techniques are likely to be employed to preprocessand analyze the multimodal data effectively. This could involve tasks such as feature extraction, dimensionality reduction, clustering, or pattern recognition across multiple modalities in Fig.2.Integration of data mining techniques involves the combination and utilization of various data mining methods and algorithms to extract meaningful insights and patternsfrom large datasets. Data mining is the process of discovering hidden patterns, relationships, and trends in data, and it plays acrucial role in various domains, including business, healthcare,finance, and marketing. By integrating different data mining techniques, organizations can enhance their decision-making processes, improve efficiency, and gain a competitive advantage.

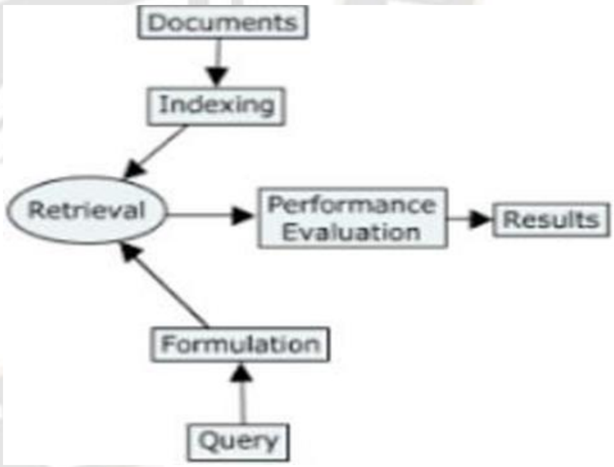

Fig. 2. Multimodal Information Retrieval Approach

One of the main advantages of integrating data mining techniques is the ability to leverage the strengths of different methods to address complex problems. Each data mining technique has its own strengths and limitations. For example, decision trees are effective for classification tasks, while clustering algorithms are suitable for identifying groups or segments within a dataset. By integrating these techniques, organizations can benefit from a more comprehensive analysis of their data. The integration of data mining techniques often involves multiple stages. The first stage is data preprocessing, which includes tasks such as data cleaning, transformation, and reduction. Data cleaning involves removing noise, handling missing values, and resolving inconsistencies in the dataset. Data transformation involves converting the data into a suitable format for analysis, such as normalization or discretization. Data reduction techniques, such as feature selection or dimen- sionality reduction, are used to reduce the complexity of the dataset.

Once the data preprocessing stage is complete, various data mining techniques can be applied. These techniques include classification, clustering, association rule mining, and anomaly detection, among others. Classification algorithms are used to predict categorical or discrete outcomes based on a set of input variables. Clustering algorithms group similar instances together based on their characteristics. Association rule mining identifies relationships or associations between different variables in the dataset. Anomaly detection techniques identify unusual or abnormal instances that deviate from the normal behavior of the data. The integration of these techniques can be achieved through ensemble methods, which combine the pre- dictions or results from multiple models to make more accurateand robust predictions. Ensemble methods, such as bagging, boosting, or stacking, can improve the performance and generalization capabilities of individual models by reducing bias and variance. Furthermore, integrating data mining techniqueswith other technologies such as machine learning, artificial intelligence, and big data analytics can further enhance the analysis process. Machine learning algorithms can be usedto build predictive models that automatically learn from the data and improve their performance over time. Artificial intelligence techniques, such as natural language processing or image recognition, can be integrated to analyze unstructured data sources like text or images. Big data analytics frameworksenable the processing and analysis of massive datasets that cannot be handled by traditional methods.

C. Integration of Deep Learning Techniques

Deep learning is a subset of machine learning that leveragesneural networks to model complex patterns and relationships within data. The study aims to incorporate deep learning algo- rithms into the multimodal information retrieval process. Deeplearning can be particularly useful in tasks such as image and speech recognition, natural language processing, and cross- modal information fusion. The integration of deep learning techniques involves the use of artificial neural networks to extract complex features and patterns from large datasets. Deep learning is a subset of machine learning that utilizes deep neural networks with multiple layers to learn hierarchicalrepresentations of data. It has gained significant attention in recent years due to its ability to solve complex problems in various domains, including computer vision, natural language processing, and speech recognition.

One of the main advantages of integrating deep learning techniques is the ability to handle large and complex datasets. Traditional machine learning techniques may struggle to ex- tract meaningful insights from such datasets due to their high dimensionality and complexity. Deep learning techniquescan effectively learn and extract features from such datasets, enabling organizations to gain valuable insights and make in- formed decisions. The integration of deep learning techniques involves several stages, including data preprocessing, model architecture design, training, and evaluation. Data preprocess- ing involves tasks such as data cleaning, normalization, and feature extraction. Feature extraction is a crucial step in deep learning as it involves extracting meaningful representationsof data that can be used by the neural network to learn fromthe data.

Model architecture design involves selecting an appropriate neural network architecture that can effectively learn from the data. There are several types of neural network architectures, including convolutional neural networks (CNNs), recurrentneural networks (RNNs), and deep belief networks (DBNs). CNNs are commonly used for image and video analysis tasks, while RNNs are suitable for sequence analysis tasks such as natural language processing. DBNs are used for unsupervised learning tasks such as feature extraction and dimensionality reduction.

Training involves feeding the neural network with input data and adjusting the weights and biases of the network to minimize the error between the predicted output and the actual output. This process is known as backpropagation, and it involves propagating the error backward through the network to adjust the weights and biases. The training process can take a significant amount of time and requires a large amount of computing resources. Evaluation involves testing the performance of the trained model on a separate dataset. This is done to ensure that the model can generalize well to new data and is not overfitting to the training data. Several metrics can be used to evaluate the performance of a deep learning model, including accuracy, precision, recall, F1 score,and area under the curve (AUC).

D. Performance Enhancement

The ultimate goal of the study is to enhance the performanceof multimodal information retrieval systems. This improve- ment can be measured in various ways, such as accuracy,efficiency, retrieval speed, or user satisfaction. By combining data mining and deep learning techniques, the study aims to achieve better results compared to traditional approaches or using either technique in isolation. Enhancing multimodal in- formation retrieval through the integration of data mining and deep learning techniques can lead to significant performance improvements. By combining the strengths of both approaches, organizations can extract more meaningful insights from multi-modal data and improve the accuracy and relevance of retrievalresults.

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Data mining techniques can be used to preprocess and analyze multimodal data, extracting relevant features and patterns from each modality. This preprocessing step is crucialin ensuring that the data is in a suitable format for deep learning models. Data cleaning, transformation, and reduction techniques can be applied to handle noise, missing values,and reduce the dimensionality of the data. Once the data is preprocessed, deep learning techniques can be employed to learn hierarchical representations and extract complex featuresfrom the multimodal data. Deep neural networks, such as convolutional neural networks (CNNs) for images or recurrentneural networks (RNNs) for sequential data, can be utilized to capture intricate relationships and dependencies within and between modalities.

The integration of data mining and deep learning techniques can be achieved through various approaches:

a) *Feature Fusion:* Features extracted from different modal-ities can be fused at different levels. Early fusion combines features at the input level, while late fusion combines features at a higher level or decision-making stage. This fusion process allows for a more comprehensive representation of the multimodal data, enabling better retrieval performance.

b) *Ensemble Methods:* Ensemble methods combine multiple models or algorithms to improve performance. By integrating data mining and deep learning models through ensemble methods such as stacking or boosting, the strengths of each approach can be leveraged, leading to enhanced retrieval accuracy and robustness.

c) *Transfer Learning:* Transfer learning allows the knowledge learned from one task or domain to be transferred and applied to another. Pretrained deep learning models on large- scale datasets can be fine-tuned or used as feature extractors for multimodal information retrieval tasks. This approach can help overcome limitations in limited labeled data or improve the efficiency of training deep learning models.

d) *Query Expansion:* Data mining techniques can be used to expand queries by incorporating relevant terms or concepts from different modalities. This expansion can improve theretrieval performance by considering a broader range of in- formation during the search process.

E. Real-world Applications

The study likely intends to provide practical insights and methodologies that can be applied to real-world scenarios. Multimodal information retrieval has numerous applications, including multimedia search engines, content-based recom- mendation systems, medical diagnosis, autonomous vehicles, and more. The research may address challenges specific to these applications.

V. RESEARCH GAP

Limited Integration of Data Mining and Deep Learning: While both data mining and deep learning techniques have been widely explored and used in various research domains, their integration specifically for multimodal information retrieval remains relatively limited. Most existing studies tend to focus on either data mining or deep learning methods individually, without fully exploiting the potential synergies that can be achieved through their combination.

Lack of Comprehensive Multimodal Datasets: The availability of large-scale and diverse multimodal datasets is crucial fortraining and evaluating integrated data mining and deep learning models for information retrieval. However, the creation and curation of such datasets are challenging and often require significant efforts. As a result, the research community faces a shortage of comprehensive and standardized datasets that encompass multiple modalities, such as text, images, audio, and video, making it difficult to conduct fair comparisons and benchmarking of new approaches.

Interpretability and explainability: Integrating data mining and deep learning techniques can lead to complex models with a large number of parameters, making the interpretability and explainability of these models a significant concern. In many real-world applications, it is essential to understand how the model arrives at its decisions, especially when dealing with sensitive domains like healthcare or finance. Addressing the trade-off between model complexity and interpretability is a crucial research gap that needs to be explored in the contextof multimodal information retrieval.

VI. RESEARCH METHODOLOGY

The proposed system takes the fractured or non-fractured digital x-ray image and pre-processes it. The pre-processed image is segmented. From the segmented image, features are extracted. These features are extracted using the multimodal approach. The multimodal approach is the combination of the Principal Component analysis (PCA), Connected Component Analysis (CCA), Hierarchical Centroid (HC) and the Blobanalysis and feature extraction. The multimodal approach also finds the percentage of the fracture and the identification of thefractured area. The feature extraction is done in the first step i.e., in the PCA and CCA, HC. Next the combined all these features and the frame difference is done. Again the feature has been extracted. Based on the double screening method the fracture has been detected. The extracted features are analysedusing data analytics techniques. The blob features are also extracted and used the data analytics to identify and detect the area of the fracture. The all the multimodal approach gives thepercentage of the fracture occurred in the hand.

Data Acquisition: The fractured and non-fractured images are stored as the database (using Radiopaedia). The images will be in the form of .jpg format. Any other format images arealso considered. But it has to be converted into the .jpg format.Some of the images are converted into the monochrome formatin Fig.3.Data acquisition is a crucial step in the data analysis pipeline. It lays the foundation for subsequent data processing,analysis, and interpretation. It is important to ensure the quality and reliability of acquired data by implementing proper validation and verification techniques. Additionally, privacy and ethical considerations should be taken into account when acquiring data to comply with legal regulations and protect sensitive information.

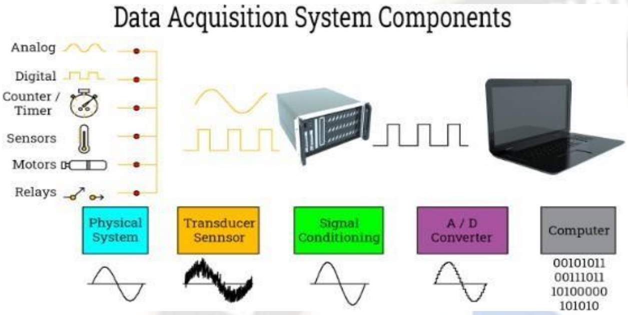


Fig. 3. Data Acquisition System

Pre-Processing: Here the image's size is resized. Noise is removed. The images undergo to the convolution techniques. The histogram is used to equalize the intensity of the image. Pre-processing is an essential step in data analysis and machinelearning tasks. It involves transforming raw data into a format that is suitable for further analysis or modeling. Pre-processing techniques aim to improve data quality, handle missing values,normalize data, and reduce noise or outliers in Fig.4.

Segmentation: To create the reference image. The water-shed and threshold segmentation algorithms are used. Mul-timodal design: In this step, the techniques such as PCA (Principal Component Analysis), CCA (Connected Component Analysis), HC (Hierarchical Component), K-means are com- bined with the segmentation techniques to extract the hidden features.

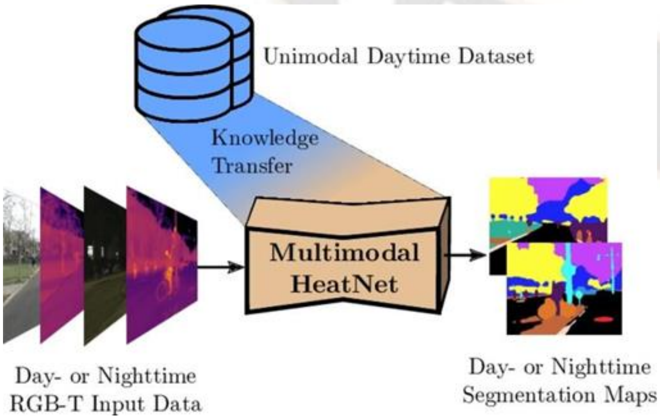


Fig. 4. Segmentation

Frame Differences: In this methodology the image differ-ence of the fractured and non-fractured are done and the resultsare analysed. In this methodology, the image difference and the hierarchical centroid techniques are used in Fig.5. Frame dif- ferences, also known as frame differencing, is a technique usedin video processing and computer vision to detect changes between consecutive frames of a video sequence. It involves subtracting the pixel values of one frame from the pixel valuesof the previous frame to highlight areas of motion or change.

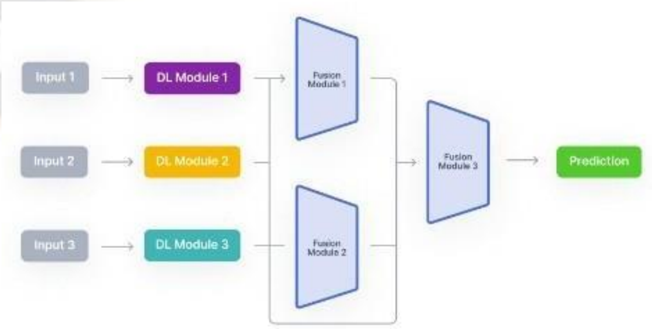
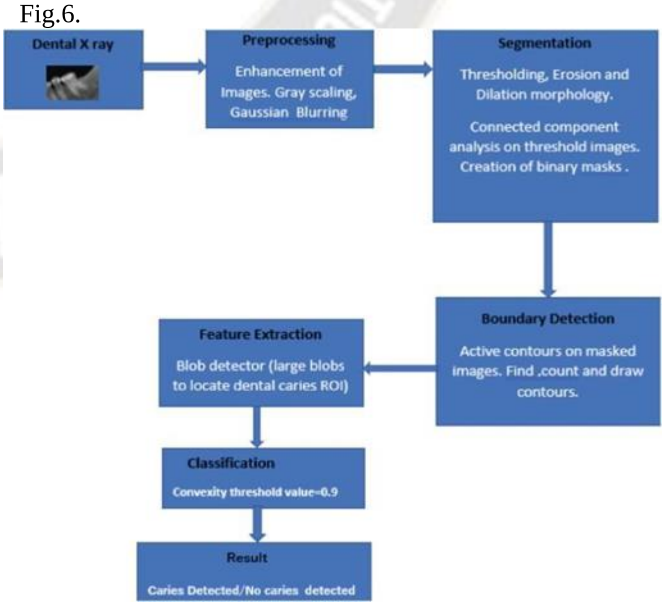


Fig. 5. Frame Differences Process

Blob Analysis and Feature Extraction: In this methodol-ogy the blob features are extracted and compared with each other and area of the fracture is identified in Fig.5. Blob analysis and feature extraction are two important techniques inimage processing and computer vision. Blob analysis refers to the process of detecting and segmenting regions of interest in an image, while feature extraction involves extracting relevantinformation or features from the segmented regions. These techniques are commonly used in various applications suchas object recognition, tracking, and surveillance. Blob analysis involves identifying and segmenting regions of interest in an image based on their intensity or color. Blobs are typically defined as connected regions of pixels with similar properties in Fig.6.



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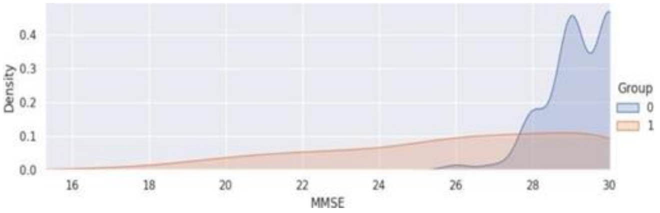

Fig. 6. Blob Analysis and Feature Extraction

Data Analytics: In this methodology the verification and validation of the multimodal and the blob analysis is done using the FRR, FAR, ERR, EA. The data analytics is also done using the confusion matrix (ACCURACY, SENSITIVITY,SPECIFICITY, and PRECESSION) and the Youden Index coefficient performance test in Fig.7.

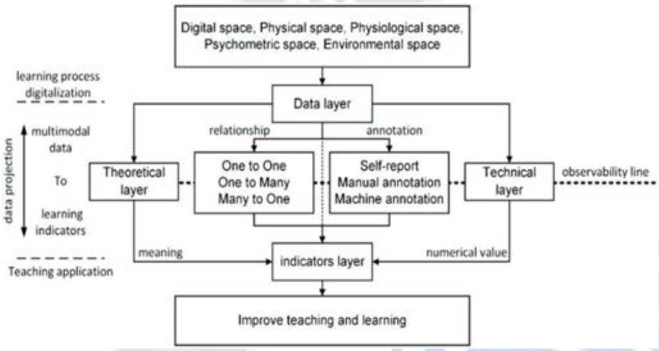

Fig. 7. A conceptual model of multimodal data analysis.

Data analytics is the process of examining and interpreting data to uncover patterns, extract insights, and make informed decisions. It involves applying various statistical and computa-tional techniques to analyze large and complex datasets. Data analytics can be applied in various domains and industries. It can help businesses optimize operations, improve customer experience, identify market trends, detect fraud, or make strategic decisions based on data-driven insights.To perform data analytics effectively, it is important to have a solid understanding of the domain, access to quality data, and proficiency in statistical analysis and programming languages such as Python or R. Additionally, data privacy and ethical considerations should be taken into account when handling sensitive or personal information.

VII. RESULTS

We use area under the receiver operating characteristic curve (AUC) as our main performance measure. We believe that in case of medical diagnostics for non-life threatening terminal diseases like most neurodegenerative diseases it is importantto have a high true positive rate so that all patients with alzheimer’s are identified as early as possible. But we also want to make sure that the false positive rate is as low as possible since we do not want to misdiagnose a healthy adult as demented and begin medical therapy. Hence AUC seemed like a ideal choice for a performance measure in fig.7.

Fig. 8. The chart shows Nondemented group got much more higher MMSEscores than Demented group

There is a performance matrix(A performance matrix, in the context of evaluating models or systems, is a visual representation or data table that displays various performance metrics and their values. This matrix is used to assess and compare the effectiveness and efficiency of different models or systems. It helps in making decisions about which model or system performs better based on specific criteria, such as accuracy, precision, recall, F1 score, or the AUC (Area Under the Curve) of a ROC curve, among others.)for each model which depicts the best between the AUC and Recall in Fig.8.

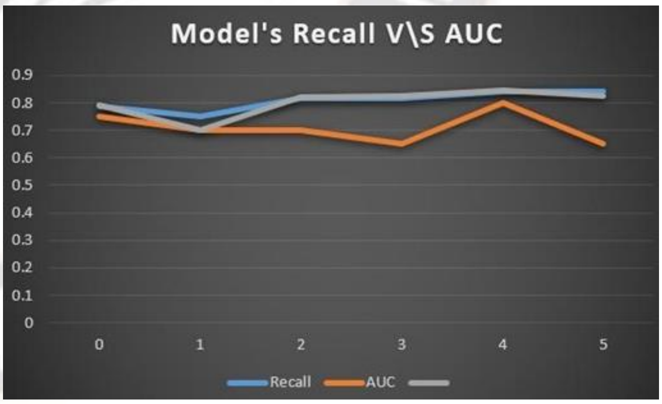

Fig. 9. Performance Metric for each model

Recall, also known as sensitivity or true positive rate, measures the ability of a model to correctly identify positive instances out of all the actual positive instances in a dataset.It is calculated as the ratio of true positives to the sum of true positives and false negatives:

Recall = True Positives / (True Positives + False Nega-tives)

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AUC, on the other hand, is a measure of the overall performance of a binary classification model across different classification thresholds. It represents the area under the Re- ceiver Operating Characteristic (ROC) curve, which plots the true positive rate (TPR) against the false positive rate (FPR)at various threshold settings.

AUC ranges from 0 to 1, with a higher value indicating better model performance. An AUC of 0.5 suggests a random classifier, while an AUC of 1 represents a perfect classifier. AUC is useful when evaluating models in scenarios where the class distribution is imbalanced or when the relative importance of false positives and false negatives varies.

A high recall indicates that the model is good at capturing positive instances and has a low false negative rate. It is particularly important in scenarios where missing positive instances (false negatives) can have severe consequences, such as in medical diagnosis or fraud detection.

To calculate recall in a multimodal setting, you would need to define what constitutes a true positive and a false negative for each modality individually. For example, in a multimodal sentiment analysis task using text and images, a true positive could be when both the text and image correctly indicate a positive sentiment, while a false negative would occur when one or both modalities fail to capture the positive sentiment.

Both recall and AUC provide important insights into the performance of a binary classification model, but they focus on different aspects. Recall emphasizes the ability to capture

positive instances correctly, while AUC provides an aggre- gated measure of overall model performance across different classification thresholds.

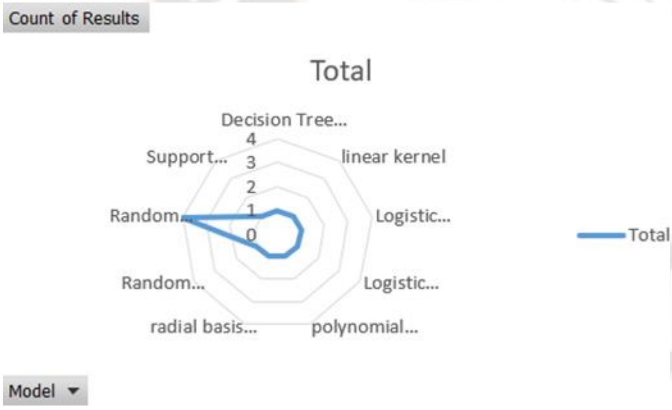

Fig. 10. Best Model Performance

Fig.10 depicts the counts of Results by each model using different methods such as Support Vector Machine(SVM), Random Forest Classifier, Radial Basis Function, Polynomial Kernel(A specific type of kernel function used in machine learning, particularly in support vector machines (SVMs)), Logistic Regression, Linear Regression, Linear Kernel, and Decision Tree and there is also a radial map which shows the best model Performance.

Fig.10 shows the Heatmap (A heat map is a graphical representation of data where values are encoded as colors to visualize patterns, relationships, or distributions. Heat mapsare commonly used in various fields, including data analysis, statistics, and machine learning. In a heat map, a color scaleis used to represent the values of a dataset. Typically, higher values are represented by warmer colors (such as red or yellow), while lower values are represented by cooler colors (such as blue or green). The intensity or brightness of the color corresponds to the magnitude of the values. Heat maps can provide valuable insights and help in data exploration and decision-making processes. They allow for quick identificationof patterns, outliers, or areas of interest in large datasets. Heat maps are often used in fields such as finance, marketing, biology, and social sciences to analyze complex data and make data-driven decisions.) for the overall data present in the modelfor the training and testing.

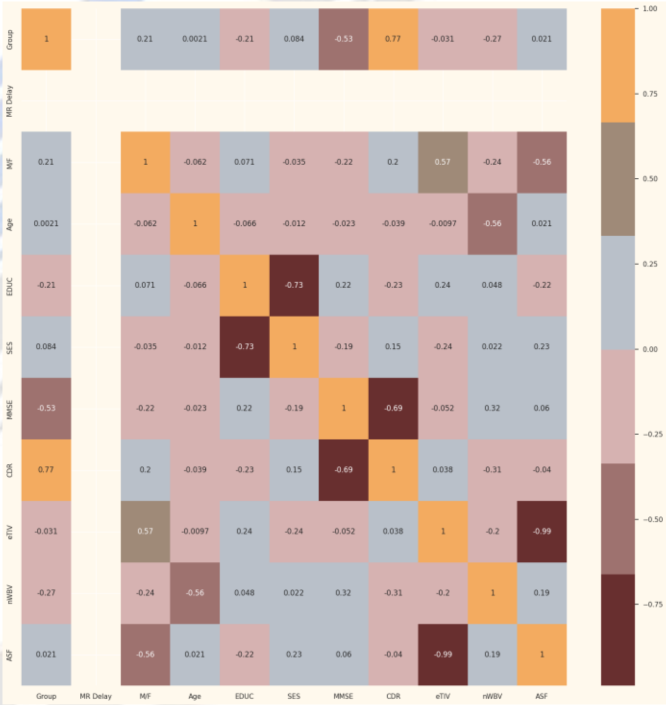

Fig. 11. Heatmap for the overall data present in the Model

Fig-12. illustrates the cluster’s Profile Based on MMSE (MMSE can refer to an estimation technique or criterion used in some machine learning algorithms, particularly in the context of Bayesian estimation.

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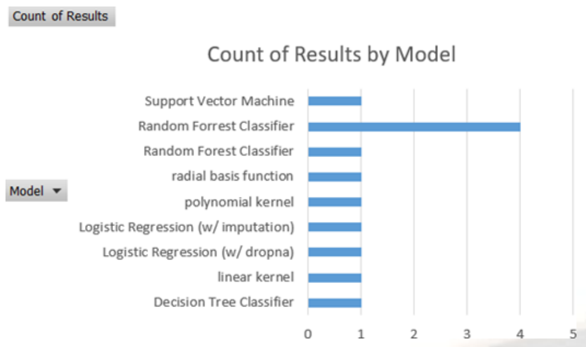

Fig. 12. Cluster's Profile Based On MMSE And SES

It aims to minimize the expected value of the squared difference between the estimated and true values.) And SES (Seasonal Exponential Smoothing. Seasonal Exponential Smoothing is a time series forecasting method that takes into account seasonality in data when making predictions. It is used toforecast future values based on historical time series data that exhibits seasonal patterns.)

The table-1 displays results from various studies using dif- ferent models and datasets for classification tasks. In the first group, E. Moradi et al. employed a Random Forest Classifier, with AUC values ranging from 61.0 percent to 94.6 percent. Yeet al. achieved an AUC of 71.0 percent and an accuracy (ACC)of 55.3 percent . For Zhang et al., the AUC was 94.6 percent, while accuracy values were not available. In the second group,Zhang et al. utilized Support Vector Machines with various kernels, achieving ACC values between 86.7 percent and 92.4 percent, although AUC values were not provided. In the third group, researchers Hyun, Kyuri, and Saurin evaluated multiple models, including Logistic Regression (with imputation or dropna), Support Vector Machines, Decision Tree Classifier, and Random Forest Classifier. Their AUC values ranged from

70.0 percent to 84.4 percent, while ACC values varied between 75.0 percent and 84.2 percent. These studies highlight the diverse model choices and performance metrics in the fieldof classification in machine learning.

Below is a comparison of our results with those from the papers that were listed previously.

TABLE I: Research Papers Output

Sr.No.	Paper	Data	Model	Results	
1.	E. Moradi et al. [3]	Ye et al. [7]	Random Forrest Classifier	AUC = 71.0%	ACC = 55.3%
		Filipovych et al. [8]	Random Forrest Classifier	AUC = 61.0%	ACC = N/A
		Zhang et al. [9]	Random Forrest Classifier	AUC = 94.6%	ACC = N/A
		Batmanghelich et al. [10]	Random Forrest Classifier	AUC = 61.5%	ACC = N/A
2.	Zhang et al. [4]	Ardekani et al. [11]	Support Vector Machine		
			polynomial kernel	AUC = N/A	ACC = 92.4%
			linear kernel	AUC = N/A	ACC = 91.5%
			radial basis function	AUC = N/A	ACC = 86.7%
3.	Hyun, Kyuri, Saurin	Marcus et al. [1]	Logistic Regression (w/ imputation)	AUC = 79.2%	ACC = 78.9%
			Logistic Regression (w/ dropna)	AUC = 70.0%	ACC = 75.0%
			Support Vector Machine	AUC = 82.2%	ACC = 81.6%
			Decision Tree Classifier	AUC = 82.5%	ACC = 81.6%
			Random Forest Classifier	AUC = 84.4%	ACC = 84.2%
			AdaBoost	AUC = 82.5%	ACC = 84.2%

VIII. CONCLUSION

The analysis is made clear that the Hierarchical Centroid Multimodal System is the best suited for the fracture detection for the wrist fracture. The hybrid approach has applied with hierarchical frame difference, uses the double time feature extraction with the other approach has also given the 100percent result when applied to the data set of 770 images. The Blob analysis and the Feature Extraction method canbe used to detect the fracture and the area of the fracture. The percentage of the fracture is estimated using all the multimodal system. The percentage of fracture is obtained with respect to the entire hand image. Comparing to the entire body and the human hand the fracture detected percentage is very small it comes in the fractions. The research would allowthe radiographers or the doctors, paramedics to recognize the fracture images and pay more focus to the patients who really need the concentration, rather than spending the lots of time in non-fractured images of the other patients. And take a course of action on the required patient. The novel system will help society and rural area where treatment is needed for saviour cases and avoid hyperkala or malunion bandages, likely to result in improper bone attachment leading to changes in bonestructure.

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