National College of Ireland

Analysis of Scalable and Efficient Approaches for Liver disease detection

MSc Research Project
Masters in Data Analytics

Akimuddin Aslam Shaikh
Student ID: x22123245

School of Computing
National College of Ireland

Supervisor: Mr. Bharat Agarwal

National College of Ireland
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School of Computing

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Student ID:	x22123245
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Analysis of Scalable and Efficient Approaches for Liver disease detection

Akimuddin Aslam Shaikh
x22123245

Abstract

The liver disease detection using machine learning has seek significant attention due to its potential to improve diagnostic accuracy and patient outcomes. This study explores an unique approach by combining texture-based features that is Gray-Level Co-occurrence Matrix (GLCM), with high-dimensional pre-trained ResNet50 deep learning model. The research aims to address gaps identified in the literature, particularly the challenge of leveraging unlabeled medical imaging datasets.

The workflow encompassed machine learning models building steps like data preprocessing, feature extraction, clustering using unsupervised techniques (KMeans, Agglomerative Clustering), and supervised classification (Random Forest, SVM, XGBoost). The classification optimization followed 6 phased approach to assess the efficacy of feature sets and clustering technique. This phase include etablishing baseline performance using extracted features from GLCM and ResNet50 features from the dataset that were tested both with Kmeans cluster and agglomerative cluster. ResNet50 features combined with Agglomerative cluster labels yielded near-perfect accuracy, achieving 99% with RF and SVM, and 100% with XGBoost outperforming ResNet50 features with KMeans labels. Among the finding, the GLCM features combined with KMeans cluster labels & agglomerative cluster labels yielded the near to perfect accuracy of 100% which indicate effective capture of the patterns in the feature but it is unusual in real-world scenario and indicated the sign of over-fitting.The study attempted to advanced the performance by Pseudo-labeling, generated from clustering, that facilitated the result of classifiers. The approach was followed by the integration of GLCM + ResNet50 features against Kmeans cluster and agglomerative clusters from which combine features of GLCM + ResNet50 with agglomerative target variable outperform kmeans target variable and enhanced classification performance, achieving up to 99% accuracy with the SVM classifier on combined features.

The results demonstrated the promising potential of combining texture and deep learning-based features in detecting liver diseases with high precision. This work provides a scalable framework for integrating diverse feature sets and contributes to the advancement of machine learning applications in medical imaging.

1 Introduction

The increasing case of liver diseases has immensely impact people's live and has emphasized the critical need for effective diagnostic tools. Due to the lack of early and reliable

detection methods, they are often diagnosed late. With advancements in imaging technologies, such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound, significant amounts of imaging data are now available. However, analyzing these images manually is both time-consuming, costly, and need to put a lot of efforts, underscoring the importance of developing automated methods for accurate analysis.

Traditional approaches mainly focused on supervised learning using annotated datasets, however, collecting labeled medical data is both expensive and resource-intensive, it makes unsupervised and semi-supervised approaches highly desirable. The rapid growth of techniques like feature extraction and advance machine learning (ML) models has opened up new routes for analyzing medical imaging data. Leveraging unsupervised machine learning technique like clustering and feature extraction engineering can reveal hidden patterns, lay the groundwork for robust classification systems and provide us with unique research.

This study focus on addressing the challenges associated with the analysis of large-scale unlabeled liver image datasets by integrating texture-based features derived from Gray Level Co-occurrence Matrices (GLCM) and deep features extracted using a pre-trained convolutional neural network (ResNet50), as demonstrated in medical imaging tasks by Hasanah et al. (2023) against cluster labels. By employing clustering methods such as DBSCAN, KMeans and Agglomerative Clustering and evaluating supervised learning models, we investigate the potential of these integrated features to identify meaningful patterns and achieve desired result.

1.1 Motivation

The research thoroughly reviewed the state of the art literature and drew inspiration from existing research. It identified the gap in the machine learning approach in context of liver disease detection and aim to address it with the approach of integrating baseline model (clusters) both with text-based features (GLCM) and pre-trained deep learning neural network (ResNet50). Finally, it aimed to integrated GLCM features and Resnet50 Features setting up kmeans and agglomerative as target variable. Unlabeled image dataset can be processed through different clustering method that can contribute in evaluation of the supervised learning models.

1.2 Research Question

The study intend to address the following research question:

- How effective is the integration of texture and deep features for clustering and classifying liver images?
- Can unsupervised clustering methods, such as DBSCAN, KMeans and Agglomerative Clustering, provide meaningful insights into large unlabeled datasets?
- How does feature integration influence the performance of supervised learning models?

1.3 Objective

Addressing the research question, the primary objective of this study are:

- To develop a feature engineering pipeline that works on texture (GLCM) and deep (ResNet50) features for liver image analysis.
- To evaluate unsupervised clustering methods and their ability to uncover latent structures with texture-based and deep learning features in the data.
- To assess the performance of supervised classifiers, such as Random Forest, SVM, and XGBoost, using the proposed integrated feature set.

1.4 Contribution

The research successfully worked on large unlabeled image dataset and contribute in following ways:

- It demonstrates the potential strengths of texture and deep features in analyzing liver images.
- It provides a systematic evaluation of different unsupervised clustering techniques on medical imaging data.
- It showcases the role of feature integration in leveraging the performance of supervised classifiers such as SVM, XGBoost and Random Forest by achieving accuracy levels of up to 99%.
- The results highlight the potential of integrating unsupervised cluster and supervised learning model for unlabeled dataset.

1.5 Structure of the paper

The paper start with the brief introduction in section 1, discussing the motivation, research question that are to be addressed and its objective, contribution of this study to data analysis. Section 2 discuss the state of the art literature that are grouped into 3 subsection and provides a thorough review, justifying the approach for this research. Section 3 is Methodology that details the steps undertaken in this study, including data preprocessing, feature engineering, clustering, and classification. Section 4 is Design Specification, which specifies the working of our system that incorporate multiple machine learning models and deep learning technique. Section 5 is implementation which talks about the execution of the proposed methodology and provides meaning insights. Section 6 is evaluation, which discusses the results from different approach conducted at different stage of research. Conclusion and Future work are discussed in Section 7.

2 Related Work

Liver disease detection has seen with significant progress and achievement with the integration of different deep learning techniques with the medical imaging analysis. This section talks about the state-of the art literature that contributed in the detection of liver disease. It focuses on medical imaging challenges, segmentation, classification, and detection methodologies to improve the research . It address both the strengths and limitations of different approaches.

The primary goal of literature review is to identify gaps in existing solutions and provide with the justification for the proposed work. The review discuss about the variety of deep learning models, imaging modalities such as CT, MRI, and ultrasound, and tasks like lesion detection, segmentation, and classification.

2.1 Imaging Techniques and Challenges in Liver Disease Detection

Survarachakan et al. (2022) comprehensively examines imaging techniques such as CT, MRI, and ultrasound and emphasizes the utility of these modalities for Detecting vessel structures, liver lesions, Preoperative planning and intraoperative ultrasound guidance. Due to poor image contrast it was a challenging task to differentiate the liver lesion from healthy liver. It Addresses issues like imaging artifacts, scanner resolution variability, and protocol differences, which had impact on diagnostic preciseness. The paper discuss the complexion of segmentation because of the variable intensity within liver parenchyma.

The integration of AI in medical imaging was explored by Zhou et al. (2019), and highlights the potential in liver disease detection and diagnosis. The paper discusses imaging modalities, that includes CT scan , MRI, and ultrasound images, and addresses the challenges associated with subjective visual assessments, such as variability in interpretation and operator dependence. The lack of curated training data, limited multi-tasking capabilities, and dependency on single-task-focused models were the main challenges in AI implementation.

2.2 Machine Learning Techniques for Liver Disease Detection

Devikanniga et al. (2020) introduced an optimized Support Vector Machine (SVM) classifier enhanced with the Crow Search Algorithm (CSA) to improve diagnostic accuracy for liver disease. The Indian Liver Patient Dataset (ILPD) from the UCI repository is used that contains both diseased and non-diseased liver samples. The study emphasizes the significance of optimization techniques, particularly CSA, which outperforms other approaches like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The authors compare this approach against multiple hybrid SVM models and demonstrate its superior diagnostic abilities through ten-fold cross-validation. The proposed CSA-SVM model acheived accuracy, specificity, sensitivity and precision of 99.49%, 98.80%, 99.76% and 99.52% respectively. The study focus on tabular datasets and our approach focuses on imaging data, exploring texture-based features like GLCM alongside deep learning models for feature extraction and clustering.

A notable work by ming Xian (2010) explores the identification of malignant and benign liver tumors using B-Mode ultrasound images, GLCM for feature extraction and FSVM for classification. The study evaluates texture features like energy, contrast, correlation, entropy, and homogeneity that averaged over four directions, providing a comprehensive analysis of liver tissue. FSVM, with a Gaussian RBF kernel, demonstrated better result with 97% accuracy and AUC of 0.984 compared to traditional SVM that had 96.3% accuracy and AUC of 0.963. This improvement is attributed to FSVM's ability to handle outliers and noise by assigning varying importance to data points during training. Variability in tumor textures, low contrast in ultrasound images, and the presence of noise highlighted the key challenges in dataset.

Rahman et al. (2019) addresses the application of traditional machine learning techniques to clinical datasets, comparing their effectiveness in predicting liver disease using the Indian Liver Patient Dataset (ILPD). It applies six supervised classification algorithms: Logistic Regression (LR), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes (NB). Logistic Regression's performance suggests its suitability for tabular data having highest accuracy of 75%, while the lower performance of Naive Bayes indicates challenges in handling complex patterns in the data. The findings highlight the need for proper feature selection and preprocessing technique to optimize model.

2.3 Deep Learning Models and Techniques for Liver Disease Detection

Gul et al. (2022) provide a comprehensive review of segmenting the liver and liver tumors from 3D volumetric medical images. It review a wide range of architectures that include CNNs, encoder-decoder models like U-Net, FCNs, ResNet, hybrid and ensemble techniques. Due to the limited availability of annotated and the tedious nature of manual labeling, robust liver tumor segmentation remains a challenge. It implements CNNs which are best suited for pixel-wise segmentation and FCNs, which perform pixel-wise segmentation without the need for dense layers. ResNet's depth enables it to capture intricate liver and tumor characteristics, proving beneficial in complex medical imaging scenario. Hybrid and ensemble techniques have been highlighted to boost segmentation and classification accuracy. Ensemble classifiers are found to be effective in liver vessel segmentation tasks. Our approach is unique in integrating unsupervised clustering (e.g., K-Means) and pseudo-labeling techniques, which reduce dependency on labeled datasets and explore novel ways to identify patterns in unlabeled data. Lakshmipriya and Pottakkat (2023) provide a detailed systematic review of deep learning techniques for liver disease diagnosis, focusing on classification, segmentation, and clinical applications. For liver segmentation tasks, U-Net and its extensions are emphasized due to its encoder-decoder framework.It Addresses challenges like limited data availability, multi-modality imaging, and variability in clinical datasets. It discusses important Deep Learning architectures (e.g., U-Net, ResNet) and their clinical relevance, evaluation metrics, and performance benchmarks in public challenges like LiTS and CHAOS. The review was conducted after summarizing 113 articles that explores research gaps and proposes directions for leveraging Deep learning models. This comprehensive analysis provides a strong foundation for developing innovative solutions to bridge the gap between technological advancements and clinical practice. Byra et al. (2018) present a comprehensive neural network-based approach for assessing nonalcoholic fatty liver disease (NAFLD) using B-mode ultrasound images. For feature extraction, the study implemented the transfer learning with a pre-trained deep convolutional neural network (Inception-ResNet-v2), combined with SVM for fatty liver classification and Lasso regression for steatosis level assessment. Despite its efficiency, the method is highly reliant on transfer learning highlighting the need for more annotated medical imaging datasets. By combining deep learning-based features with texture-based features (e.g., GLCM), our work expands on Byra's approach, offers a richer feature representation. This study by Rahman et al. (2022) focus on Fully automated liver and tumor segmentation using a hybrid ResUNet model. The study leverages CT image volumes, such as low contrast between liver tissue and neighboring organs and variability in tumor size and shape, to address potential issue in segmenting liver and tumor

regions. Advanced preprocessing techniques like histogram equalization and Hounsfield unit windowing were utilized to enhance contrast and remove noise. The hybrid ResUNet model combined ResNet and UNet architectures to achieve high segmentation accuracy up to 99.6% and a dice coefficient of 99.2% for tumor segmentation. The study by Chou et al. (2021) provides insights on non-invasive detection and classification of fatty liver disease severity using B-mode ultrasound images. It emphasizes model optimization and preprocessing techniques like parameter tuning with the ultrasound images. It evaluates multiple pretrained CNN models (e.g., ResNet-50, VGG19) for feature extraction and highlights the effectiveness of deep learning in improving diagnostic accuracy. The paper discusses image challenges like operator dependency in ultrasound, motion artifacts, and machine-based variation. The research uses accuracy, sensitivity, specificity and ROC-AUC demonstrating robust evaluation techniques. It shed lights on effectiveness of deep learning models, showcasing their ability to extract rich features and improve diagnostic accuracy in liver disease detection. However, this research attempts to integrate GLCM with ResNet50-derived features and leveraging unsupervised clustering.

3 Methodology

The methodology section provide comprehensive details of the adopted research methodology to fulfill the addressed research question and its objective. This includes everything from explanation of the techniques, tools, and procedures utilized, ensuring the reproducibility of code and research analysis of the work. The research attempts to bridge the gaps that are identified from the literature review, and work on the unique approach of integrating texture-based features (GLCM) and deep learning-based features (ResNet50) for clustering and classification in liver disease detection. It addresses the challenge of working with unlabeled medical image datasets and implements supervised learning models to derive meaningful pattern and insights through clustering and pseudo-labeling strategies. Furthermore, integrating these approaches with supervised learning improved the model's ability to handle complex imaging data effectively.

3.1 Data Collection

For this research, an unlabeled liver image dataset is used from the kaggle website. The dataset is in .jpg format, consisted of 19261 images,and organize in different subfolders, that are named in order like volume_1, volume_2,... volume_130. The dataset was then uploaded to the google drive and implemented the dataset on google Colab Pro environment. This is the dataset link: https://www.kaggle.com/datasets/anassbenfares/liver-images/data.

3.2 Data preprocessing

Preprocesing step in machine learning and deep learning is very essential to understand the dataset nature and to tailor it according to the requirement. The workflow diagram in Figure 1 shows the preprocessing approach for this research.

Following are the data preprocessing approach for this project:

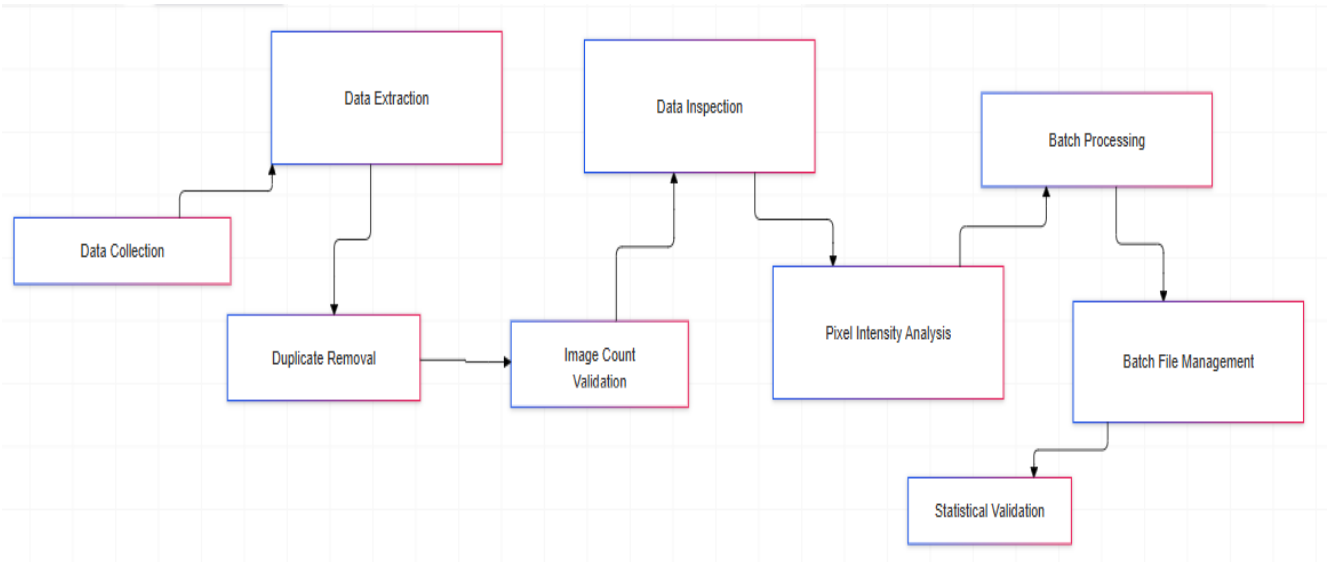

Figure 1: Preprocessing Approach

3.2.1 Data Extraction:

The dataset was zipped file and consisted of image files located at many different subfolders. It would be time-consuming to access file from each subfolders everytime. So, it was first unzipped and organized the dataset into a consolidated folder for easy access. All images were moved from subfolders to a single directory to streamline processing.

3.2.2 Duplicate Removal and Image Count Validation :

To identify and remove duplicate images, we calculated file hashes to ensures unique data points and verified the total number of images after consolidation and duplicate removal.

3.2.3 Data Inspection:

To ensure image quality and consistency we visualized random samples from the dataset. The loaded images are depicted in Figure 2 and provide us with valuable insights.

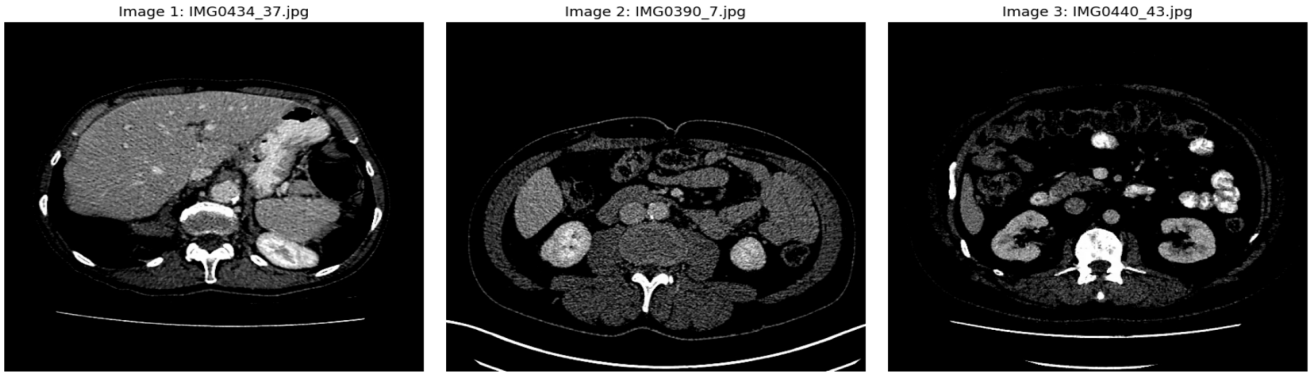

Figure 2: Random Sample Liver images

3.2.4 Pixel Intensity Analysis:

Analyzed pixel intensity distribution across the dataset to identify potential inconsistencies and the need for normalization. The pixel intensity distribution graph in Figure 3 shows that the majority of the pixel values are close to 0, indicating that most of the image regions are dark or have low intensity and just a small fraction of pixel values reach the maximum intensity (1), indicating the presence of bright or high-intensity regions.

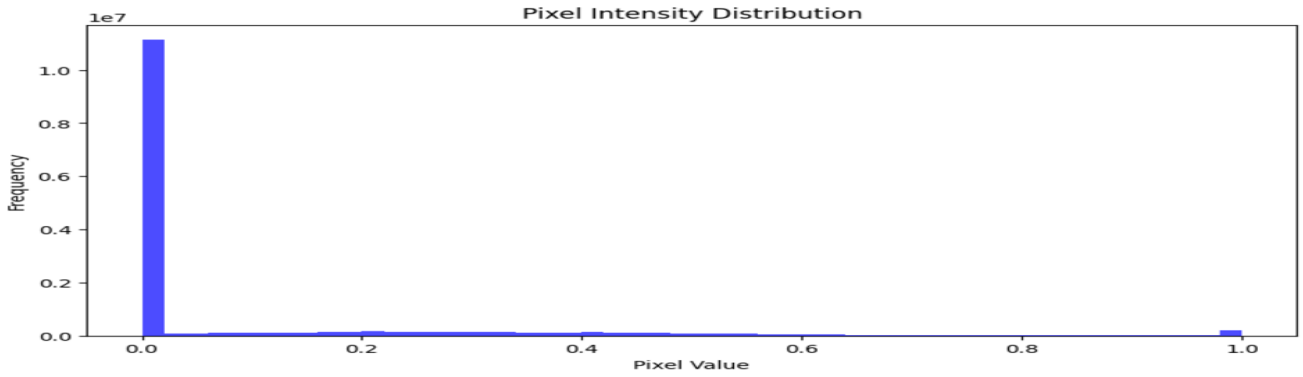

Figure 3: Pixel Intensity Distribution

3.2.5 Batch Processing & Batch File Management:

To ensure consistency, we resized all the images to 224x224 pixels, as recommend by Li and Rai (2020) for compatibility with ResNet50, which require a fixed input size. It makes the dataset compatible with the deep learning models like ResNet50, which require a fixed input size. Then we normalized pixel values to a range of [0, 1] that helps improving the model performance by accelerating convergence during training and reducing the impact of varying contrast across images. Finally, saved preprocessed images into batches of 500 for efficient processing and storage that reduces memory overhead. After batch preprocessing, we ensured that batch files were stored systematically and avoided redundant processing by checking for existing preprocessed files.

3.2.6 Statistical Validation:

The final step include, verification of batch shapes and contents for consistency and correctness across preprocessing steps. Figure 4 shows the location and shape of few batch files.

```
Batch 1: /content/drive/My Drive/dataset_folder/preprocessed_data/batch_6.npy
Shape: (500, 224, 224, 3)
Batch 2: /content/drive/My Drive/dataset_folder/preprocessed_data/batch_7.npy
Shape: (500, 224, 224, 3)
Batch 3: /content/drive/My Drive/dataset_folder/preprocessed_data/batch_8.npy
Shape: (500, 224, 224, 3)
```

Figure 4: batch file Location and shape

3.3 Features Extraction:

3.3.1 Texture-Based Feature Extraction (GLCM):

The Gray-Level Co-occurrence Matrix (GLCM), demonstrated by Javidan et al. (2023) and in diagnosing grape leaf diseases, was used to extract texture features such as contrast, correlation, homogeneity, dissimilarity and energy. In liver disease detection, these characteristics are very useful for capturing textural differences because they offer a quantitative assessment of the spatial correlations between pixel intensities. This technique works well for analyzing the structural patterns seen in datasets related to medical imaging.

3.3.2 Deep Learning-Based Feature Extraction (ResNet50):

The ResNet50 model, a pre-trained convolutional neural network, as demonstrated by Hasanah et al. (2023) was used for feature extraction. By utilizing the model's global average pooling layer, we extracted high-dimensional feature vectors that encapsulate semantic information about the images. ResNet50's depth and skip connections enable it to capture complex patterns and its hierarchical features makes it ideal for medical image analysis.

These techniques were integrated both with the cluster label and with each other to enhance both low-level texture information (from GLCM) and high-level semantic features (from ResNet50), creating a promising representation for subsequent clustering and classification tasks.

3.4 Clustering and Labeling:

3.4.1 Unsupervised Clustering Methods:

- KMeans Clustering:

  KMeans Algorithm, as successfully demonstrated by Ripon et al. (2021) for anomalies detection, was used to cluster the feature representations obtained from GLCM and ResNet50 features. The images were grouped into 5 distinct clusters to identify potential patterns or subgroups within the dataset. This method was chosen for its simplicity, speed, and effectiveness in handling high-dimensional data. Figure 5 shows the KMeans clustered distribution of 19261 image files into 5 distinct clusters. These values are grouped heterogeneously, where certain clusters (e.g., 1 and 3) dominate, while others (e.g., 0 and 4) represent less frequent but potentially unique feature patterns.

  After clustering, 5 images from each clusters were loaded to ensure consistency in visualization and the clustered files were then stored in .npy format at a specific location to access it easily during the reproducibility (re-run) saving a lot of processing time.

  The KMeans PCA graph in Figure 6 depicts the formation of cluster by KMeans algorithm in a 2D space, where dimensionality was reduced using PCA for better visualization, as shown by Priyanka and Kumar (2020), who achieved better accuracy by reducing GLCM-derived features for kidney ultrasound images. All the clusters are visually distinct in the plot, indicating that the KMeans algorithm was able to segment the dataset into groups with unique feature patterns. Mostly the

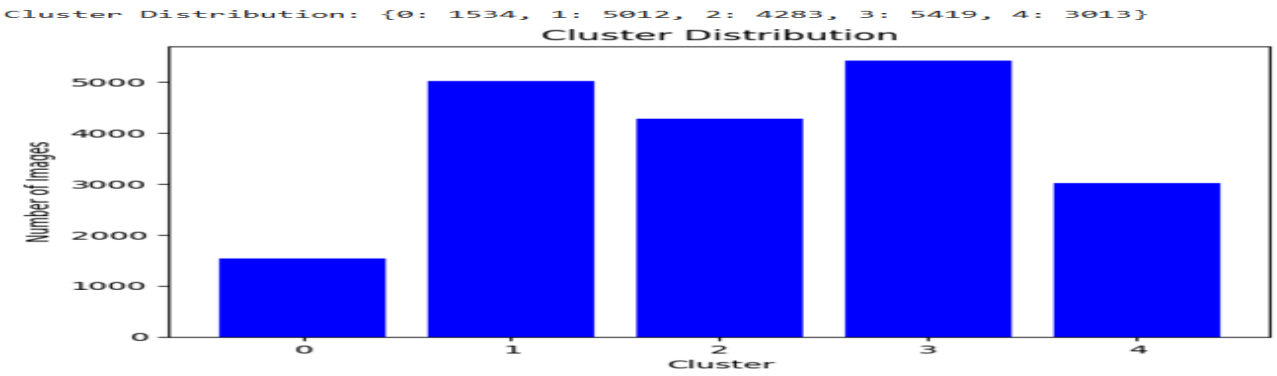

Figure 5: KMeans Clustered distribution

clusters are distinct, but still some overlap are visible, suggesting potential similarities in feature distributions or noise in the data. The size of each cluster corresponds to the number of data points assigned to it. Larger clusters dominate the graph, while smaller clusters are more compact.

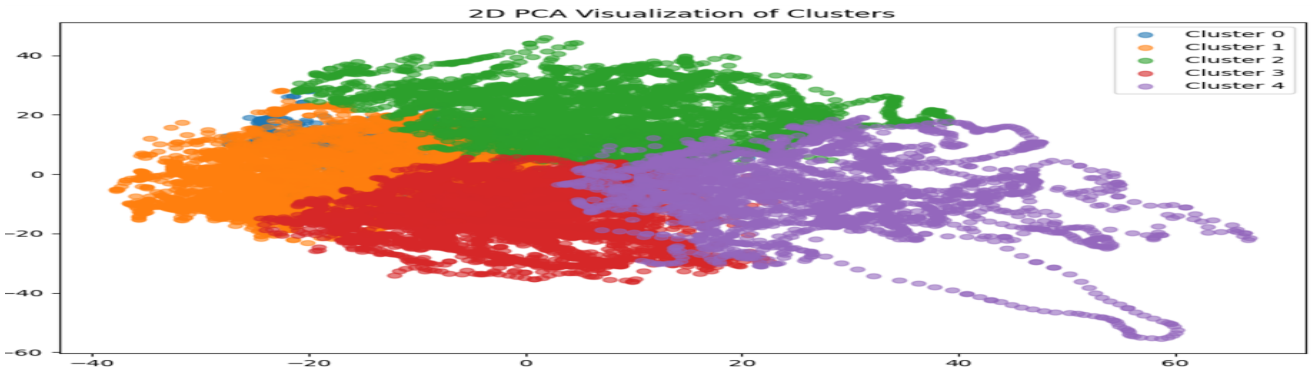

Figure 6: 2D PCA visualization

- DBSCAN Clustering: DBSCAN was attempted because of its robust nature in identifying arbitrary-shaped clusters and handling noise, as demonstrated by Bandyopadhyay and Paul (2013) to effectively segment noisy medical images. However, it failed to form meaningful clusters in this dataset, as most data points were noisy. This was likely due to the high dimensionality of the feature space and the chosen hyperparameters.

  Figure 7 provides with the insight of scattered distribution of points without clear cluster boundaries in a 2D t-SNE reduced dimensional space enabling visualization of high-dimensional data in a low-dimensional space, as shown by Poličar et al. (2019). The parameters used for DBSCAN were likely not optimal for this dataset's structure. It was ineffective for this specific dataset and feature space due to its dependence on density thresholds, which does not align with the datasets characteristics.

- Agglomerative Clustering: This hierarchical clustering technique was inspired from Chi et al. (2010), which highlights the potential of clustering for medical image

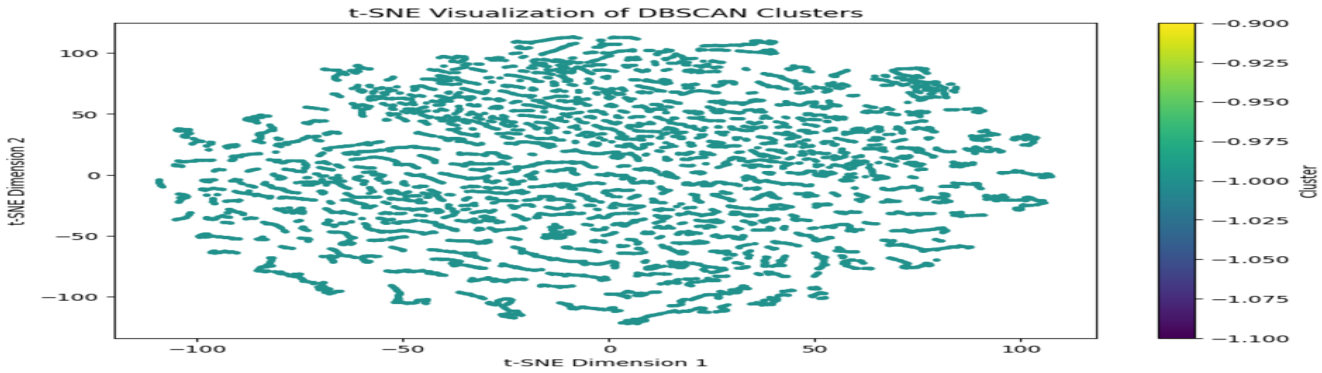

Figure 7: t-SNE Visualization of DBSCAN Clusters

analysis and applied to explore data grouping without assuming cluster shapes and similar to KMeans, it successfully grouped the data into 5 clusters. T-SNE visualization was used to project high-dimensional data into 2D space for better interpretability of the clustering.

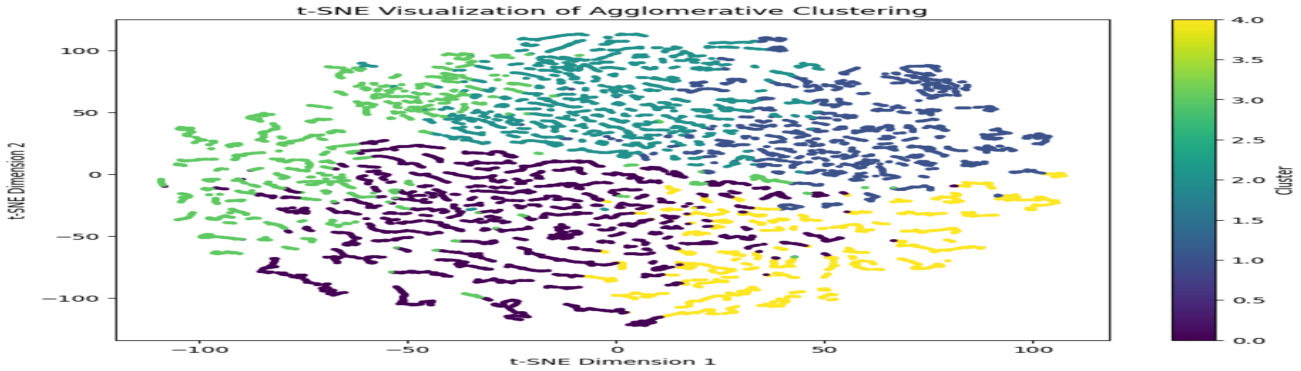

Figure 8: t-SNE Visualization of Agglomerative Clusters

Figure 8 shows that how successfully it segmented the data into 5 unique meaningful groups as indicated by color-coded region. The clusters are appeared to be relatively compact, with some overlap between adjacent clusters, which might indicate shared or similar feature spaces. The visual representation of Agglomerative cluster algorithm depicts that some clusters are more dispersed (e.g., yellow cluster), while others (e.g., purple cluster) appear more tightly packed. This could indicate variability in feature distributions.

3.4.2 Generation of Cluster Labels and Pseudo-Labeling:

To pseudo-label the data for supervised learning tasks, cluster labels were used. These pseudo-labels allowed the integration of unsupervised learning outcomes into supervised classification, filling the gap created by the lack of original ground truth labels. The generated pseudo-labels facilitated model training with methods like Random Forest, SVM, and XGBoost, that contributes to the performance evaluation of the models.

3.5 Approach to Classification Optimization

This section discusses the step taken to enhance the model performance with the unique approach in each phase.

3.5.1 Independent Feature Analysis with cluster labels

- ResNet50 Features with Cluster Labels: ResNet50 was employed to extract high-dimensional features from the dataset. Transfer learning was utilized by freezing the initial layers of ResNet50 while using its later layers to derive feature representations. The extracted ResNet50 features were clustered using KMeans to generate cluster labels. The clusters were used as pseudo-labels, allowing the dataset to simulate labeled data for supervised classification. Similarly, hierarchical clustering was applied to the ResNet50 features, generating another set of pseudo-labels. The hierarchical nature of Agglomerative Clustering aimed to capture structural relationships in the data. The features were then normalized using Standard Scaler to ensure consistency in input scale. The final dataset was split into training (80%) and testing (20%) subsets for model evaluation.

- GLCM Features with Cluster Labels: The Gray-Level Co-occurrence Matrix (GLCM) was employed to derive texture-based features from the dataset. Key features included contrast, energy, correlation, dissimilarity and homogeneity. The GLCM-derived features were clustered using KMeans, generating pseudo-labels that were aligned with the partitioning structure of the clustering algorithm and was inspired from a technique supported by Hum et al. (2011) for combining GLCM with K-Means for medical image segmentation. Agglomerative Clustering was applied to the GLCM features to identify latent groupings. The hierarchical clustering approach aimed to explore the alignment of texture-based features with structural groupings in the dataset. Similar to ResNet50, the GLCM features were normalized and split into training and testing subsets for supervised classification. By employing both ResNet50 and GLCM features with KMeans and Agglomerative Clustering, the methodology aimed to evaluate the compatibility of these features with different clustering labels. This independent feature analysis laid the solid foundation for indepth analysis of feature-cluster relationships and provided a basis for further experimentation.

3.5.2 Feature Integration and Final Classification

To achieve optimal performance, GLCM and ResNet50 features were combined to form a comprehensive feature set. This combined feature set aimed to improve both the spatial texture information (from GLCM) and the high-dimensional representational power of deep learning (from ResNet50). The integration enhanced the dataset's richness, providing a diverse representation that could be better utilized by supervised classification models. The combined feature set was clustered using KMeans, generating pseudo-labels for supervised classification. The partitioning approach of KMeans aimed to capture separable clusters in the combined feature space. Agglomerative Clustering was applied to the combined feature set to explore its alignment with structural relationships in the data. Similar to the above step, the integrated feature set was normalized using Standard Scaler and the data was then split into training and testing subsets, maintaining an 80:20 ratio.

This integrated approach was critical to understanding how texture and deep learning features complement each other. The methodology demonstrated the potential to achieve robust classification performance across different clustering techniques.

3.6 Evaluation Technique

The strength and accuracy of the methodology were validated using a range of statistical and performance evaluation techniques:

3.6.1 Clustering Evaluation:

- Silhouette Score: It was used to evaluate the performance of DBSCAN clustering method. The purpose was to assess how well DBSCAN grouped the data points based on their features. A higher silhouette score indicates well-defined clusters. However, for this research, Silhouette score did not contribute much. This might be likely due to the points in a cluster are far from each other. Figure 9 display the Silhouette score for DBSCAN.

```
Number of clusters: 0
Silhouette Score: N/A
```

Figure 9: Silhouette Score

- Cluster Distribution Analysis: It was used to evaluate the balance of image assignments across clusters to ensure diversity in pseudo-labels. The distribution of cluster in KMeans is represented in Figure 5 and for agglomerative, it is displayed in Figure 10.

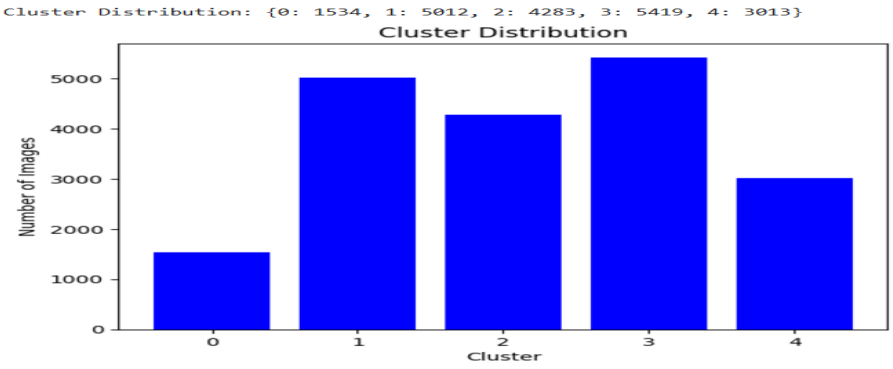

Figure 10: Agglomerative Cluster Distribution

3.6.2 Classification Metrics:

Accuracy was used to calculate the ratio of correctly classified instances to the total number of instances. It was used to compare the performance of Random Forest, SVM, and XGBoost models. The effectiveness of SVM with the RBF kernel in medical images has been demonstrated by Singh and Kaur (2012) achieving 100% accuracy with

GLCM-based features for brain MRI images. Precision, Recall, and F1-Score metrics were analyzed from classification reports to assess model performance across different classes, especially in handling imbalanced data.

3.6.3 Visualization Techniques:

- t-SNE and PCA: Dimensionality reduction techniques was applied to visualize high-dimensional feature distributions and cluster separations. The diagram for the t-SNE is displayed in Figure 7 and Figure 8 and the visualization for PCA is shown in Figure 6
- Pixel Intensity Analysis: To validate the preprocessing steps and ensure consistency in data, the research examined the pixel value distributions across the dataset. The visuals for the same is depicted in Figure 3

3.6.4 Statistical Validation:

Cross-Validation: Performed to ensure the reliability of classification results across multiple subsets of data. Comparison Across Models: Results from Random Forest, SVM, and XGBoost were compared on standalone and combined feature sets to validate the improvement provided by the integrated approach ensuring a consistent evaluation framework.

4 Design Specification

The design of our system incorporates multiple machine learning and deep learning techniques to address the difficulties in liver disease detection. This approach integrate texture-based analysis and transfer learning with unsupervised clustering and supervised classification. The key components of the design include preprocessing pipelines, feature extraction techniques, clustering and labeling, and classification models. The workflow for the same is depicted in Figure 11

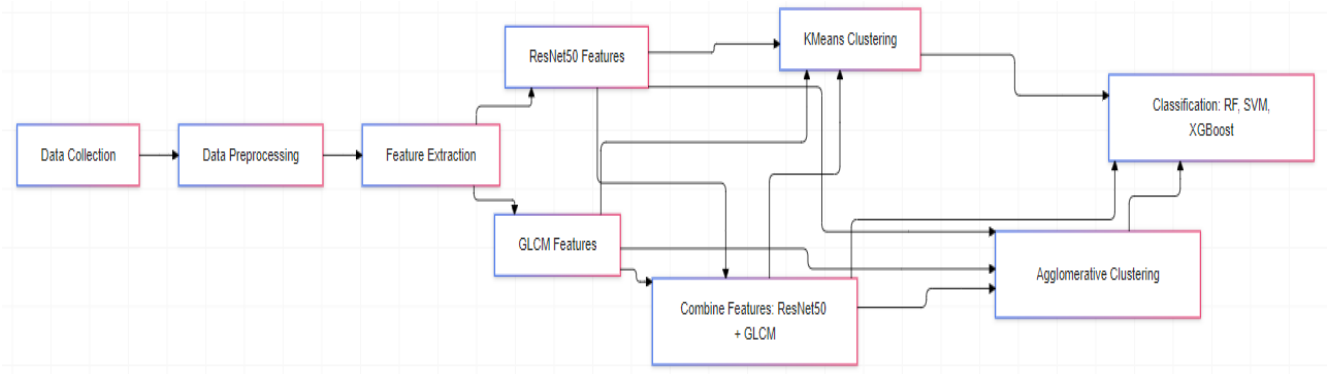

Figure 11: Design for liver disease detection

The approach starts with a preprocessing technique by resizing images to 224x224 pixels and normalized to the range [0, 1] for consistency and computational efficiency as there were more than 19000 images data. Later, The preprocessed images are stored

in batches to optimize memory utilization and processing speed. This design ensures scalability for handling large datasets.

Gray-Level Co-occurrence Matrix (GLCM) and ResNet50 (deep learning features) approaches were implemented for feature extraction. The reason for choosing GLCM is because of its ability to capture spatial texture properties such as contrast, correlation, dissimilarity, energy, and homogeneity, which are critical for analyzing medical images. ResNet50 is employed as a feature extractor through transfer learning. The initial approach includes working on GLCM AND ResNet50 features with KMeans and Agglomerative cluster labels independently. The final dataset feature are combined from GLCM and ResNet50 features against KMeans and Agglomerative cluster labels, that provides a comprehensive representation of both texture-based and deep learning-based features.

The pseudo-labels were generated for supervised learning by applying Clustering to the extracted features. Three Clustering techniques like KMeans, DBSCAN, and agglomerative were used. KMeans and Agglomerative Clustering are the primary methods used, with t-SNE and PCA applied for dimensionality reduction and visualization. DBSCAN was also explored but found to be incompetent for this dataset due to the irregular density of clusters.

Supervised classification models, including Random Forest, SVM, and XGBoost, are integrated into the design to evaluate the models performance. The classification process initially uses raw features, then, cluster labels and is subsequently refined by combining GLCM and ResNet50 features against cluster labels. A train-test split with an 80-20 ratio ensures robust evaluation. The accuracy of the classifier were improved by Hyperparameter tuning and cross-validation. The results demonstrating significant improvement when using combined features.

The proposed design emphasizes modularity, scalability, and integration of unsupervised and supervised methodologies. It attempts to bridge the gap between old-fashioned texture-based analysis technique and deep learning approaches, making it a robust framework for liver disease detection. This comprehensive design forms the backbone of our implementation and ensures systematic handling of the data, features, and models to achieve optimal results.

5 Implementation

The implementation phase of the project involves executing the proposed methodology that provides meaningful results. It ensures that each component works cohesively. Below is an overview of the steps and tools utilized during this stage:

5.1 Final Data Preparation:

The preprocessed dataset was segmented into training and testing sets. The GLCM features and ResNet50-derived features worked on cluster label independently. Later, in the final stage, GLCM and ResNet50 features were combined and perform against kMeans and agglomerative independently to form a feature set for classification tasks.

5.2 Feature Extraction Outputs:

GLCM extracted Texture-based features such as contrast, correlation, energy, dissimilarity and homegenity for spatial texture analysis. Deep learning features were extracted using a ResNet50, a pretrained convolutional network model, with transfer learning enabling robust representation without requiring extensive retraining. Both of the feature sets were saved as .npy files for streamlined access during modeling.

5.3 Clustering and Labeling:

Unsupervised clustering techniques, including KMeans and Agglomerative Clustering, were applied to label the unlabeled dataset into unique groups. The generated cluster labels were included into the supervised learning stage as pseudo-labels to guide classification.

5.4 Classification Models:

Supervised classifiers like Random Forest, SVM, and XGBoost, were implemented to evaluate the combined feature set. These models were selected based on their robust performance in classification tasks and their ability to handle high-dimensional data effectively. Outputs of classification were calulate using evaluation metrics like precision, recall, and accuracy scores, with the combined feature set yielding significantly improved results.

5.5 Tools and Technologies:

Python language was used for its extensive libraries and frameworks for machine learning and image processing. Libraries like TensorFlow and scikit-learn were used for ResNet50 ,and clustering and classification respectively. tqdm was used for progress tracking and matplotlib for visualization. The implementation was conducted on Google Colab Pro to leverage cloud resources and ensure reproducibility.

5.6 Visualization Outputs:

The results were represented through detailed visualizations, including pixel intensity distribution, PCA projections, and t-SNE cluster representations, providing insights into the dataset and the efficacy of clustering methods.

6 Evaluation

This section critically evaluates the results through different experiments conducted at different stages of the research. Each experiment is designed to address specific aspects of the research objectives and to validate the proposed methodology. Following are the evaluation approach:

6.1 Experiment 1: Clustering Analysis

To categorize unlabeled liver image dataset into meaningful clusters, we evaluate the effectiveness of unsupervised clustering techniques (KMeans, Agglomerative Clustering,

DBSCAN). From the research it was concluded that KMeans produced balanced clusters, as shown in the Figure 6, with clear separations observed in the PCA visualization. On other hand,Agglomerative Clustering provided comparable results to KMeans with similar cluster distributions displayed in Figure 10 and t-SNE visualizations as shown in Figure 8. However, DBSCAN failed to form meaningful clusters due to the high dimensionality and sparsity of the data, and resulted in a low silhouette score. The clustering results provided diverse pseudo-labels, which were crucial for downstream supervised classification.

6.2 Experiment 2: GLCM and ResNet50 Feature Analysis

To capture essential patterns for classification tasks, the study analyze the effectiveness of texture-based (GLCM) and deep learning-based (ResNet50) features. GLCM captured spatial texture properties, including contrast, correlation,dissimilarity, homogenity, and energy, that were vital for analyzing liver tissues. ResNet50 features (extracted via transfer learning) represented complex image characteristics with high dimensionality, offering a complementary feature set to GLCM. The combination of GLCM and ResNet50 features established a robust representation of liver images, bridging gaps in single-feature approaches.

6.3 Experiment 3: Supervised Classification

6.3.1 Independent Feature Analysis with Clustering Labels:

- ResNet50 + KMeans: This was the first approach of the prject to integrated ResNet50 features with KMeans and Kmeans cluster labels were set as target variable instead of dummy label. It resulted in Random Forest obtaining 88%, SVM for 87%, XGBoost getting 100%. It highlighted moderate performance improvements but suggested a bit lack of alignment between ResNet50 features and KMeans clustering.

- ResNet50 + Agglomerative: The second approach was to experiment and compare the model performance with KMeans by combining ResNet50 features with Agglomerative Cluster labels. It resulted in Random forest and SVM scoring 99% and XGBoost getting 100% accuracy. It showcase the excellent alignment between ResNet50 features and hierarchical clustering, yielding near-perfect accuracy.

- GLCM + KMeans: The third approach was to integrated texture based features with KMeans cluster labels. It resulted in all the model scoring 100% and indicated potential overfitting, as all models achieved perfect accuracy, warning of the risk of overly simplified pseudo-labels.

- GLCM + Agglomerative: The fourth approach was to verify the texture based features with other cluster labels as it resulted in potential overfitting state with KMeans cluster. However, it acheived similar result as that of our third approach resulting all the model obtaining 100% for all models. It achieved perfect accuracy but raised similar concerns about overfitting with texture-based features.

6.3.2 Integrated Feature Analysis:

- Combined GLCM + ResNet50 with Agglomerative: This was the fifth approach for

our project and the reason was to reveal pattern for integrated features of GLCM and ResNet50 with Cluster labels. GLCM was combined with ResNet50 feature setting Agglomerative as target variable results in Random forest scoring 97%, SVM scoring 99% and XGBoost scoring 98%. It demonstrated the power of feature integration, with complementary properties of GLCM and ResNet50 features capturing spatial textures and deep image representations.

- Combined GLCM + ResNet50 with KMeans: This was the final attempt of the research to combine the GLCM and ResNet50 features with Kmeans cluster labels. For this approach, Random Forest acheived 78%, SVM scored 81% and XGBoost resulted in 80% accuracy. It Achieved moderate performance but indicated suboptimal alignment between combined features and KMeans clusters.

6.4 Discussion

The study worked on 6 main approach that leads to a progress in understanding the relationship between texture-based (GLCM) and deep learning-based (ResNet50) features for liver disease detection. Each experiment provided critical insights into clustering, feature integration, and supervised learning models. The combined feature approach outperformed individual methods, achieving high classification accuracies.

6.4.1 Experiment 1: Clustering Analysis

KMeans provided balanced clusters, as observed in the cluster distribution analysis, while Agglomerative Clustering offered slightly better cohesion for smaller clusters. DBSCAN failed due to the high dimensionality and density of the feature space. The integration of PCA before clustering helped in dimensionality reduction, which is important for handling high-dimensional datasets. Also, Cluster distribution analysis revealed balanced and meaningful clustering insights, critical for pseudo-labeling. however, the failure of DBSCAN highlights the challenges of working with noisy datasets, which could have been addressed through hyperparameter tuning or alternate clustering algorithms. The clusters lacked validation through external benchmarks, as no ground-truth labels were available. The Future work could explore advanced clustering techniques like Gaussian Mixture Models (GMM) or deep clustering methods for better results in high-dimensional spaces.

6.4.2 Experiment 2: GLCM and ResNet50 Feature Analysis

This experiment demonstrated the complementary nature of GLCM texture features and ResNet50 deep learning features. GLCM captured spatial textures, while ResNet50 provided semantic feature extraction through transfer learning. The combination of these features led to a rich display of image characteristics, addressing the variability in texture and intensity. The batch processing of GLCM features ensured efficiency in handling large datasets, but were prone to data leakage or over-fitting. GLCM feature extraction was limited to predefined properties and ResNet50's dependancy on pretrained weights may not fully align with the specific nature of liver disease imaging data. Future research in this context could be investigation of other deep learning models like EfficientNet for feature extraction and Fine-tuning ResNet50 on a domain-specific dataset could improve feature relevance.

6.4.3 Experiment 3: Supervised Classification

Supervised classification provided with significant achievement in precision as the study advanced through various approaches. The integration of ResNet50 features with Agglomerative cluster labels and GLCM features with KMeans cluster labels resulted near to perfect accuracy for Random Forest, SVM, and XGBoost classifiers and highlights the effectiveness of aligning appropriate features with clustering methods. The final combined feature set (ResNet50 + GLCM), when performed with Agglomerative cluster labels, demonstrated the value of integrating texture-based and deep learning features which achieve accuracies of 97%, 99%, and 98% for Random Forest, SVM, and XGBoost, respectively.

When features were used independently, such as ResNet50 with KMeans and GLCM with Agglomerative, offered moderate improvements but highlighted the need for robust feature representations. Notably, GLCM with KMeans clustering and GLCM with Agglomerative clustering achieved 100% accuracy across all classifiers raised concerns of potential overfitting and the risks of overly simplified pseudo-labels. These results underscore the importance of evaluating model performance against real-world applicability.

The findings emphasize the transformative potential of feature integration and clustering-based pseudo-labeling in improving classification performance. Future research could explore ensemble techniques that combine predictions from multiple classifiers to enhance robustness further, or apply transfer learning with domain-specific fine-tuning to reduce over-fitting risks. Additionally, testing the methodology on different medical imaging datasets would provide insights into the generalizability of the proposed approach The overall result from the research is depicted in Figure 12

Approach	Feature Set	Target Variable	Random Forest Accuracy (%)	SVM Accuracy (%)	XGBoost Accuracy (%)
1. ResNet + KMeans	**ResNet50 Features + KMeans Labels**	**KMeans Labels**	**88**	**87**	**100**
2. ResNet + Agglomerative	**ResNet50 Features + Agglomerative Labels**	**Agglomerative Labels**	**99**	**99**	**100**
3. GLCM + Agglomerative	**GLCM Features + Agglomerative Labels**	**Agglomerative Labels**	**100**	**100**	**100**
4. GLCM + KMeans	**GLCM Features + KMeans Labels**	**KMeans Labels**	**100**	**100**	**100**
5. ResNet + GLCM + Agglomerative	**Combined ResNet50 + GLCM Features**	**Agglomerative Labels**	**97**	**99**	**98**
6. ResNet + GLCM + KMeans	**Combined ResNet50 + GLCM Features**	**KMeans Labels**	**78**	**81**	**80**

Figure 12: Model Performance

6.4.4 Contextualization with Literature

This study addresses the challenges associated with large-scale unlabeled liver image datasets by combining GLCM and ResNet50, leveraging insights from existing literature. Hasanah et al. (2023) demonstrated the efficacy of ResNet50 in medical imaging, guiding

its use for extracting deep features in this study. Following Li and Rai (2020), all images were resized to 224x224 pixels to ensure compatibility with ResNet50. GLCM-based texture analysis, validated by Javidan et al. (2023) in diagnosing grape leaf diseases, was employed to derive features like contrast, correlation, energy, dissimilarity and homogeneity. Clustering techniques, including K-Means Ripon et al. (2021), Agglomerative clustering Chi et al. (2010), and DBSCAN Bandyopadhyay and Paul (2013) were applied for feature grouping and anomaly detection, highlighting their flexibility across medical domains. Dimensionality reduction methods, such as PCA Priyanka and Kumar (2020) and t-SNE Poličar et al. (2019), were utilized for visualizing feature clusters in 2D space. The combined use of GLCM and K-Means for segmentation was inspired by Hum et al. (2011), and the demonstrated effectiveness of SVM with GLCM-based features was inspired by Singh and Kaur (2012), reinforce the robustness of this study's hybrid approach for liver disease detection.

6.4.5 Scalability Challenges

- Computational Cost of ResNet50 Feature Extraction : The ResNet50 model is powerful but requires high computational resources for feature extraction because of its deep architecture and large number of parameters. Extracting features from large datasets can be time-intensive, potentially hindering scalability for real-time applications.
- Need for Powerful Hardware GPU Requirement: High-performance hardware like GPUs or TPUs can be used for the processing of ResNet50 features on large datasets to handle computations efficiently. Limited memory on standard hardware can result in bottlenecks, especially when dealing with high-resolution images or large batch sizes.

7 Conclusion and Future Work

This study attempted to answer the critical research questions that include integration of texture-based and deep learning-based features for clustering and classifying liver images, the usage of unsupervised clustering technique on large unlabeled datasets, and the influence of feature integration on the performance of supervised learning models. By addressing these questions, the research aimed to develop a feature engineering pipeline combining texture (GLCM) and deep learning (ResNet50) features for liver image analysis. It evaluated unsupervised clustering methods like KMeans, Agglomerative Clustering, and DBSCAN for their ability to reveal latent structures in large unlabeled datasets and assess supervised classifiers, such as Random Forest, SVM, and XGBoost, using the integrated feature set.

The research provide meaningful analysis for KMeans and Agglomerative Clustering that have successfully grouped unlabeled images into meaningful clusters, while on the other hand, DBSCAN struggled with the high dimensionality of the data. Cluster distribution analysis revealed balanced image allocations, providing a strong foundation for pseudo-labeling.

Supervised Classification: A clear progression was observed in classifier performance across the different approaches:

- ResNet50 Features with KMeans Labels: ResNet50 features when combined with KMeans labels achieved 88% accuracy with Random Forest, 87% with SVM, and 100% with XGBoost, showcasing an improvement instead of using dummy labels but iy highlights the potential challenges of aligning ResNet50 features with partitioning-based clustering.

- ResNet50 Features with Agglomerative Labels: ResNet50 features combined with Agglomerative labels yielded exceptional performance, with Random Forest and SVM achieving 99% accuracy and XGBoost achieving 100%. This demonstrates the effective alignment of ResNet50 features with the hierarchical clustering structure.

- GLCM Features with Agglomerative Labels: GLCM features with Agglomerative labels achieved 100% accuracy for all three classifiers. This indicates that GLCM features align well with hierarchical clustering structures, capturing spatial texture effectively. however, it also warn about the potential over-fitting or data leakage.

- GLCM Features with KMeans Labels: GLCM features with KMeans labels also achieved 100% accuracy across all models, suggesting potential over-fitting or over-alignment of GLCM features with KMeans clusters.

- Combined GLCM and ResNet50 Features with Agglomerative Labels: The integration of GLCM and ResNet50 features with Agglomerative labels provided strong performance, with Random Forest, SVM, and XGBoost achieving 97%, 99%, and 98% accuracy, respectively, showcasing the complementary nature of texture and deep features.

- Combined GLCM and ResNet50 Features with KMeans Labels: Combining GLCM and ResNet50 features with KMeans labels resulted slightly lower performance compared to Agglomerative, achieving 78% with Random Forest, 81% with SVM, and 80% with XGBoost, indicating a less optimal alignment of combined features with KMeans clusters.

The findings demonstrate that integrating texture-based features and deep learning-derived features with unsupervised clustering methods can provide with valuable insights and contribute uniquely in a research for both unsupervised clustering and supervised classification methods. This approach bridges the gap between traditional texture analysis and modern deep learning techniques, and thus making it a valuable contribution to liver disease detection research. The success of clustering methods also highlights the potential for pseudo-labeling to utilize large unlabeled datasets effectively.

The project did experience some drawbacks like the failure of DBSCAN that underlines the need for better dimensionality reduction or alternative clustering algorithms. The dependancy on pseudo-labels generated from unsupervised clustering limits the generalizability of findings without external validation. ResNet50 was used without domain-specific fine-tuning, which might have restricted its relevance to liver image characteristics.

The future work in context of this research would likely to explore methods like Gaussian Mixture Models (GMM) or deep clustering algorithms to improve clustering accuracy and adaptability to high-dimensional data. Domain adaptation techniques can be implemented to train the model on multiple datasets that would enable it to generalize across different imaging modalities. Hybrid techniques, such as combining clustering with neural

network-based auto-encoders, can be investigated to uncover latent patterns in large image datasets. Incorporate domain-specific labeled datasets to validate the performance of pseudo-labeling and feature integration. Using transfer learning approaches to fine-tune the model on datasets with varying imaging characteristics. The study can be extended to combine features from multiple imaging modalities (e.g., CT, MRI, ultrasound) for a more comprehensive diagnostic framework. Optimize the pipeline for processing in real-time by incorporating lightweight models (e.g., MobileNet, EfficientNet) for feature extraction.

By addressing these areas, future research can build upon the foundation laid by this study, advancing the capabilities of machine learning and deep learning methods in medical imaging analysis.

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