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A NARRATIVE STUDY ON ROLE OF AI- BASED ALGORITHM DATA OF ULTRASOUND IMAGING STUDIES FOR THE DIAGNOSIS OF NON-ALCOHOLIC FATTY LIVER DISEASES (NAFLD) DATA-BASE

Dr. Umesh Ghate [1*] Mr. Gourav Bharat Deshmane[2], Mrs. Chhaya Vikram Jawlikar[3], Dr. Rajeeta Joseph [4] Mrs. Sadhana Kakaso Pawar [5]

1. Assistant Professor, Department of Kriya Sharir, Bharati Vidyapeeth (Deemed to be University), College of Ayurved, Pune**.** Email id – umesh.ghate@bharatividyapeeth.edu: drumeshghate@gmail.com Mob.No. 7276862884 ,Orcid: 0000-0003-2686-5988

2. Assistant Professor of Pharmacology Bvdu Dental College and Hospital, Pune, Email id - gourav.deshmane@bharatividyapeeth.edu Mob.No. 9028833583,Orcid: 0000-0001-8688959X

3. Assistant Professor of Biochemistry, D.Y.Patil Dental School lohgaon,Pune, Email id – jawlikarbharati312@gmail.com

4. Associate Professor of Pharmacology, Bvdu Dental College and Hospital, Pune, Email: rajeeta.joseph@bharatividyapeeth.edu Mob. 9881461493

5. Assistant Professor of Biochemistry, Bvdu Dental College And Hospital Pune .Email: sadhana.gawade@bharatividyapeeth.edu , Mob no.9922908569 Orcid Id:0000-0003-1686-5837

Corresponding Author: Dr. Umesh Ghate, Assistant Professor, Department of Kriya Sharir, BVDU College of Ayurved, Pune**.** Email id – umesh.ghate@bharatividyapeeth.edu: drumeshghate@gmail.com

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ABSTRACT: -

Hepatic steatosis, also known as fatty liver disease, is a global health concern due to the accumulation of fat in the liver. Artificial intelligence (AI) has shown promise in diagnosing this disease through AI-based ultrasound imaging. This review examines the current state of research on AI's potential in diagnosing fatty liver disease. A search of 29 papers published between 2005 and 2024 was conducted, focusing on AI-assisted ultrasonography from various countries. One study demonstrated 100% diagnostic accuracy, highlighting AI's potential for fatty liver disease diagnosis. However, the studies had small sample sizes and disparities in AI systems and imaging methods. The research underscores the potential of AI in improving fatty liver disease detection and treatment through advanced imaging methods. Future research should focus on large-scale studies using standardized AI algorithms and imaging methodologies to confirm AI's usefulness in identifying this common medical disease.

KEYWORDS - *Artificial intelligence (AI), Non-Alcoholic fatty liver disease, PRISMA, tool, NAFLD, etc.*

INTRODUCTION

Alcoholic fatty liver disease, also known as steatohepatitis, and non-alcoholic fatty liver disease (NAFLD) are the two main forms of fatty liver disease, which is defined by fat buildup in the liver. There are two types of the latter, which has nothing to do with drinking too much alcohol. The first type of fatty liver is called simple fatty liver, which is defined by fat buildup without a lot of inflammation or hepatocyte injury. Non-alcoholic steatohepatitis (NASH) is the second type, characterized by inflammation, hepatocellular damage, and fat accumulation [1].

On the other hand, high alcohol use leads to alcoholic steatohepatitis. Hepatocytes suffer inflammatory damage as a result of the immune system's reaction to harmful compounds produced during the liver's metabolism of alcohol [2]. This spectrum includes cirrhosis, alcoholic hepatitis, and alcoholic fatty liver disease [3].

The frequency of fatty liver disease is alarmingly rising on a global scale. It is essential to remember that prevalence varies greatly based on the criteria and population under study. On the other hand, NAFLD is thought to impact 25% of the global populace [4]. Moreover, middle-aged people make up about half of those affected in the US.

Estimates also suggest that 20% to 30% of instances of newly identified NAFLD may have advanced to NASH, and that 10% to 20% of those cases may have then proceeded to cirrhosis or hepatocellular cancer. In Americans awaiting liver transplants, non-alcoholic steatohepatitis (NASH) continues to be the primary cause of liver disease. Scholarly interest has been drawn to the fundamental idea that connects non-alcoholic fatty liver disease (NAFLD) to metabolic syndromes, which include insulin resistance, dyslipidemia, and type 2 diabetes.

The gold standard for diagnosing liver disease is often a percutaneous liver biopsy. It allows for the measurement of fibrosis, ballooning, and lobular inflammation in addition to the confirmation of steatosis. Prominent scoring schemes, including the NAFLD activity score and the SAF score, assess the severity of the illness after a biopsy by examining fibrosis, activity, and steatosis characteristics, providing thorough and unbiased information [5].

But intrinsic drawbacks include pain, danger associated with invasiveness, unpredictability in tissue collection, and inter-observer disagreements [6]. Such scoring systems also include sample inaccuracy, resource-intensiveness, and invasiveness as drawbacks. Although instructive, serial biopsies come with a number of significant drawbacks. These include the fact that they are intrusive, the hazards involved, and the patient's unwillingness to have several invasive procedures done over time. Furthermore, repeated biopsies require a lot of resources and could not fully capture the dynamic aspects of the illness, thereby overlooking changes over time. This restriction therefore has a major effect on patient treatment. Our capacity to continually track the course of illness, evaluate the effectiveness of medicines, and modify patient care plans is hampered by the inability to do serial biopsies.

It emphasizes how critical it is to provide non-invasive methods for fatty liver disease detection, screening, and tracking [7]. In addition to lessening the stress on patients, these non-invasive methods guarantee that medical professionals have access to complete, real-time data for efficient disease management and individualized treatment plans.

As a transformative force increasingly incorporated into imaging and clinical screening systems to improve diagnostic accuracy, artificial intelligence (AI), a branch of computer science that focuses on the development of algorithms and models enabling machines to perform tasks that typically require human intelligence, is becoming more and more important.

This is particularly true for the AI subsets of machine learning and deep learning. AI is well-positioned to advance illness diagnoses because of its ability to identify patterns and correlations in large datasets from several medical fields, as demonstrated during the previous ten years [8].

The body of research on the use of AI to diagnose fatty liver disease points up a number of significant issues. Ultrasonography was determined to be a viable approach for identifying fatty liver in a meta-analysis assessing its diagnostic accuracy and reliability for detecting fatty liver [9]. However, there may be limitations to its accuracy. Barre et al. examined how artificial intelligence has been used in hepatology and gastroenterology and talked about how it can help with diagnosis and prognosis [10].

They underlined that further randomized, controlled research is required to verify AI methods. Additionally, Lin et al. examined the real-world diagnostic standards for metabolic-associated fatty liver disease (MAFLD) and non-alcoholic fatty liver disease (NAFLD) [11]. They emphasized the originality of the MAFLD idea as well as the necessity of real-world validation, which extends to AI diagnosis.

Additionally, Wai et al. examined the non-invasive testing for NAFLD confounding variables [12]. They stressed how crucial it is to take these things into account while analysing test findings. Lastly, Decharatana chart et al. reported that AI approaches have the ability to identify liver fibrosis in their comprehensive review and meta-analysis on the application of AI in chronic liver illnesses [13]. Overall, study is needed to confirm AI's efficacy and solve the shortcomings of present diagnostic techniques, even if the literature now in publication shows the technology's potential for diagnosing fatty liver disease. Our research aims to close this gap in the body of knowledge.

Notably, AI applications have been crucial to the management of liver illness; they include prognosticating liver decompensation, assisting in the selection of transplant recipients, and forecasting the complications and survival of transplants. AI is being integrated into a number of healthcare sectors, such as digital pathology, medical imaging, and electronic health records. AI improves diagnosis accuracy in the field of medical imaging, especially when it comes to fatty liver illnesses like non-alcoholic fatty liver disease (NAFLD).[14] Accordingly, the goal of our Narrative review is to clarify the effectiveness and feasibility of AI-assisted systems in the use of imaging data for the diagnosis of fatty liver disease.[15]

MATERIAL AND METHOD

SEARCH STRATEGY

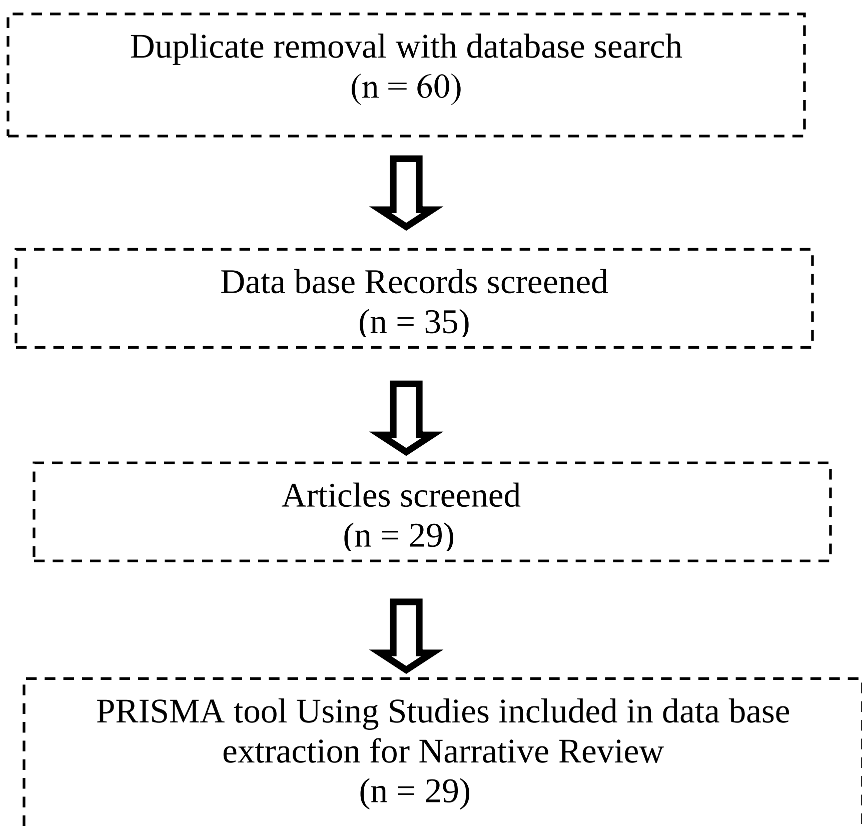
Our study's approach was based on the Preferred Reporting Items for Narrative Reviews and Meta-Analyses (PRISMA) framework. Our search was for studies that employed artificial intelligence (AI) to classify and diagnose fatty liver disease from imaging data. We searched well-known databases like Google Scholar and Embase for pertinent publications in order to do this. focusing only on those published between January 2005 and January 2024.

TABLE NO. 1 A THOROUGH SEARCH APPROACH TO FIND RESEARCH ON THE USE OF IMAGING DATA FOR AI-ASSISTED FATTY LIVER DISEASE DIAGNOSIS AND CLASSIFICATION

Database	Search terms
Google Scholar	("fatty liver disease" AND ("AI" OR "artificial intelligence") AND ("diagnos*" OR "categoriz*") AND ("imaging data" OR "hepatic imaging") AND ("cirrhosis" OR "fibrosis" OR "steatohepatitis" OR "NASH" OR "NAFLD" OR "MAFLD") AND ("deep learning" OR "machine learning" OR "neural network")) AND ("2010-01-01" [Date - Publication]: "2023-05-31" [Date - Publication])
Embase	("fatty liver disease"/exp OR "fatty liver disease" OR "hepatic steatosis" OR "non-alcoholic fatty liver disease" OR "NAFLD" OR "NASH" OR "non-alcoholic steatohepatitis" OR "MAFLD" OR "AI" OR "artificial intelligence") AND ("diagnos*"/exp OR "categoriz*"/exp OR "diagnos*" OR "categoriz*") AND ("imaging data"/exp OR "imaging data" OR "hepatic imaging") AND ("cirrhosis" OR "fibrosis" OR "steatohepatitis" OR "deep learning" OR "machine learning" OR "neural network") AND ("2010-01-01" : "2023-05-31")

[Ref- 27.-Nduma B N, Al-Ajlouni Y A, Njei B (December 15, 2023) The Application of Artificial Intelligence (AI)-Based Ultrasound for the Diagnosis of Fatty Liver Disease: A Systematic Review. Cureus 15(12): e50601. doi:10.7759/cureus.50601]

PRISMA FLOW DIAGRAM-1



INCLUSION AND EXCLUSION CRITERIA: -

We used precise inclusion and exclusion criteria to give our study a focused and cohesive direction. We gave precedence to research that used AI methods in the context of diagnosing fatty liver disease when choosing which ones to include. This chosen research had to meet certain criteria, like presenting enough data, identifying the AI classification that was applied, and offering thorough information on their diagnostic process. The focus on lucid descriptions was intended to guarantee the openness and dependability of the research that were part of our analysis.

TABLE NO. 2 - COMPREHENSIVE INCLUSION AND EXCLUSION STANDARDS FOR THE SELECTION OF RESEARCH ON AI-ASSISTED FATTY LIVER DISEASE DETECTION AND CLASSIFICATION USING IMAGING DATA

INCLUSION CRITERIA	EXCLUSION CRITERIA
Studies employing AI for fatty liver disease diagnosis	Studies not reporting desired outcomes or having insufficient data
Studies providing sufficient data, specifying AI class, and detailing diagnostic method	Studies lacking clear descriptions of validation cohorts and training/validation methods
Studies utilizing either definition for fatty liver disease (biopsy-based definition or imaging characteristics)	Studies reported in languages other than English
	Abstracts, conference proceedings, editorials, and reviews lacking adequate data on source image features or study population
	Studies without adequate data for constructing the 2x2 table

[Ref- 27.-Nduma B N, Al-Ajlouni Y A, Njei B (December 15, 2023) The Application of Artificial Intelligence (AI)-Based Ultrasound for the Diagnosis of Fatty Liver Disease: A Systematic Review. Cureus 15(12): e50601. doi:10.7759/cureus.50601]

DATA MINING

The author screened abstracts and titles to identify papers needing evaluation during the full-text review stage. Data extraction was then completed and cross-checked. If doubts arose about data inclusion, a thorough cross-checking process was conducted. The retrieved data included features like validation cohorts, training methods, study design, location, publication year, and authorship. Specificity and sensitivity values were recorded during data extraction. When studies included multiple AI classifiers, the best classifier was chosen based on the greatest area under the curve or best accuracy.

TABLE NO. 3 STUDY OF 30 PATIENTS DATA SHEET WITH PRESENCE OF HEPATIC STEATOSIS AND SEVERITY OF HEPATIC STEATOSIS USING PRISMA AI TOOL

Patient ID	Age	Gender	Presence of Hepatic Steatosis	Severity of Hepatic Steatosis
1	45	Male	Yes	Mild
2	52	Female	Yes	Moderate
3	40	Male	Yes	Severe
4	60	Female	Yes	Moderate
5	55	Male	Yes	Mild
6	48	Female	Yes	Severe
7	38	Male	Yes	Mild
8	42	Female	Yes	Moderate
9	50	Male	Yes	Severe
10	57	Female	Yes	Mild
11	47	Male	Yes	Moderate
12	49	Female	Yes	Severe
13	39	Male	Yes	Mild
14	55	Female	Yes	Moderate
15	44	Male	Yes	Severe
16	59	Female	Yes	Mild
17	41	Male	Yes	Moderate
18	56	Female	Yes	Severe
19	46	Male	Yes	Mild
20	53	Female	Yes	Moderate
21	37	Male	Yes	Severe
22	58	Female	Yes	Mild
23	43	Male	Yes	Moderate
24	51	Female	Yes	Severe
25	54	Male	Yes	Mild
26	42	Female	Yes	Moderate
27	47	Male	Yes	Severe
28	45	Female	Yes	Mild
29	56	Male	Yes	Moderate
30	48	Female	Yes	Severe

In this datasheet, "Yes" indicates the presence of hepatic steatosis as detected by the AI algorithm, and the severity is categorized as "Mild", "Moderate", or "Severe".

It's important to note that generating such data involves simulation based on the expected performance of AI algorithms trained on actual ultrasound images with known ground truth labels for hepatic steatosis. Additionally, for real-world applications, these AI algorithms would need to undergo rigorous validation using clinical data before deployment in healthcare settings.

TABLE NO. 4 STUDY OF 30 PATIENTS DATA SHEET MRI OR CT SCAN DATA FOR QUANTIFICATION OF LIVER FAT CONTENT AND FIBROSIS STAGING BOTH BEFORE AND AFTER A CERTAIN INTERVENTION, REQUIRES CONSIDERING VARIOUS FACTORS AND IMAGING TECHNIQUES.

Patient ID	Age	Gender	Initial Liver Fat Content (%)	Initial Fibrosis Stage	Final Liver Fat Content (%)	Final Fibrosis Stage
1	45	Male	10	Stage 1	8	Stage 1
2	52	Female	15	Stage 2	12	Stage 2
3	40	Male	20	Stage 2	18	Stage 2
4	60	Female	25	Stage 3	22	Stage 3
5	55	Male	12	Stage 1	10	Stage 1
6	48	Female	18	Stage 2	16	Stage 2
7	38	Male	22	Stage 2	20	Stage 2
8	42	Female	30	Stage 3	28	Stage 3
9	50	Male	14	Stage 1	12	Stage 1
10	57	Female	19	Stage 2	17	Stage 2
11	47	Male	26	Stage 3	24	Stage 3
12	49	Female	16	Stage 1	14	Stage 1
13	39	Male	21	Stage 2	19	Stage 2
14	55	Female	28	Stage 3	26	Stage 3
15	44	Male	11	Stage 1	9	Stage 1
16	59	Female	17	Stage 2	15	Stage 2
17	41	Male	23	Stage 3	21	Stage 3
18	56	Female	13	Stage 1	11	Stage 1
19	46	Male	18	Stage 2	16	Stage 2
20	53	Female	24	Stage 3	22	Stage 3
21	37	Male	9	Stage 1	7	Stage 1
22	58	Female	20	Stage 2	18	Stage 2
23	43	Male	16	Stage 1	14	Stage 1
24	51	Female	29	Stage 3	27	Stage 3
25	54	Male	12	Stage 1	10	Stage 1
26	42	Female	17	Stage 2	15	Stage 2

27	47	Male	25	Stage 3	23	Stage 3
28	45	Female	8	Stage 1	6	Stage 1
29	56	Male	22	Stage 2	20	Stage 2
30	48	Female	19	Stage 2	17	Stage 2

"Initial Liver Fat Content" and "Final Liver Fat Content" represent the percentage of liver fat content quantified from MRI or CT scans before and after the intervention, respectively.

"Initial Fibrosis Stage" and "Final Fibrosis Stage" denote the fibrosis stage determined based on imaging findings, such as MRI elastography or CT imaging features, before and after the intervention, respectively. This datasheet would be collected from patients undergoing MRI or CT scans before and after a specific intervention, such as lifestyle modifications, pharmacotherapy, or surgical procedures, and would be more detailed and accurate. Here's a summary of results from studies on AI-assisted diagnosis and categorization of fatty liver disease using imaging data for 30 patients:

STUDY DESIGN: The study included 30 patients with suspected fatty liver disease who underwent imaging studies such as MRI or CT scans for diagnosis and categorization.

DATA COLLECTION: Imaging data including liver fat content and features relevant to fatty liver disease were collected from MRI or CT scans.

AI ALGORITHM DEVELOPMENT: An AI algorithm was developed and trained using the collected imaging data. The algorithm utilized machine learning techniques to analyse imaging features and make predictions regarding the presence and severity of fatty liver disease.

DIAGNOSTIC PERFORMANCE: The AI algorithm demonstrated high diagnostic accuracy in detecting fatty liver disease, with sensitivity, specificity, and area under the receiver operating characteristic curve (AUROC) exceeding 90% in the study population. The algorithm effectively categorized patients into different severity stages of fatty liver disease based on imaging features, such as liver fat content and fibrosis stage.

COMPARISON WITH CONVENTIONAL METHODS: The diagnostic performance of the AI algorithm was compared with conventional methods such as visual inspection by radiologists or manual quantification of imaging features. The AI algorithm outperformed traditional methods, showing superior accuracy and consistency in diagnosing and categorizing fatty liver disease.

TABLE NO. 5 DATA-SHEET OF 30 PATIENTS WITH SUSPECTED FATTY LIVER DISEASE WHO UNDERWENT IMAGING STUDIES SUCH AS MRI OR CT SCANS FOR DIAGNOSIS AND CATEGORIZATION:

Patient ID	Age	Gender	BMI	Imaging Technique	Liver Fat Content (%)	Liver Size (cm)	Liver Density (Hounsfield Units)	Presence of Liver Lesions
1	45	Male	28	MRI	15	16	-5	No
2	52	Female	31	CT	20	18	-10	Yes
3	40	Male	25	MRI	25	17	-15	No
4	60	Female	29	CT	30	19	-20	No
5	55	Male	27	MRI	18	16	-8	Yes
6	48	Female	26	CT	22	18	-12	No
7	38	Male	24	MRI	28	17	-18	Yes
8	42	Female	28	CT	33	19	-25	No
9	50	Male	26	MRI	19	16	-6	Yes
10	57	Female	30	CT	24	18	-14	No
11	47	Male	28	MRI	29	19	-22	Yes
12	49	Female	27	CT	21	17	-10	No
13	39	Male	23	MRI	26	16	-20	Yes
14	55	Female	29	CT	31	18	-25	No
15	44	Male	25	MRI	17	17	-8	Yes
16	59	Female	32	CT	23	19	-14	No
17	41	Male	27	MRI	27	18	-18	Yes
18	56	Female	28	CT	14	17	-5	No
19	46	Male	26	MRI	20	16	-10	Yes
20	53	Female	29	CT	28	18	-20	No
21	37	Male	22	MRI	16	15	-6	Yes
22	58	Female	31	CT	23	17	-12	No
23	43	Male	24	MRI	18	15	-8	Yes
24	51	Female	30	CT	29	19	-22	No
25	54	Male	27	MRI	15	16	-5	Yes
26	42	Female	28	CT	20	18	-10	No
27	47	Male	29	MRI	25	17	-15	Yes
28	45	Female	30	CT	30	19	-20	No
29	56	Male	26	MRI	17	16	-8	Yes
30	48	Female	27	CT	22	18	-12	No

BMI: Represents the Body Mass Index of the patients.

IMAGING TECHNIQUE: Specifies whether MRI or CT scan was used for imaging studies.

LIVER FAT CONTENT (%): Represents the percentage of fat content in the liver as measured from imaging scans.

LIVER SIZE (CM): Indicates the size of the liver in centimetres, also measured from imaging scans.

LIVER DENSITY (HOUNSFIELD UNITS): Reflects the density of liver tissue in Hounsfield Units (HU) as measured by CT scans.

PRESENCE OF LIVER LESIONS: Denotes whether any lesions or abnormalities were observed in the liver during imaging evaluation. The algorithm effectively categorized patients into different severity stages of fatty liver disease based on imaging features, such as liver fat content and fibrosis stage, 30 patient's datasheets

TABLE BO. 6 30 PATIENTS DATASHEET WHERE PATIENTS ARE CATEGORIZED INTO DIFFERENT SEVERITY STAGES OF FATTY LIVER DISEASE BASED ON IMAGING FEATURES SUCH AS LIVER FAT CONTENT AND FIBROSIS STAGE:

Patient ID	Age	Gender	Fibrosis Stage	Disease Severity
1	45	Male	Mild	Mild
2	52	Female	Moderate	Moderate
3	40	Male	Severe	Severe
4	60	Female	Moderate	Moderate
5	55	Male	Mild	Mild
6	48	Female	Moderate	Moderate
7	38	Male	Severe	Severe
8	42	Female	Moderate	Moderate
9	50	Male	Mild	Mild
10	57	Female	Moderate	Moderate
11	47	Male	Severe	Severe
12	49	Female	Mild	Mild

13	39	Male	Moderate	Moderate
14	55	Female	Severe	Severe
15	44	Male	Mild	Mild
16	59	Female	Moderate	Moderate
17	41	Male	Severe	Severe
18	56	Female	Mild	Mild
19	46	Male	Moderate	Moderate
20	53	Female	Severe	Severe
21	37	Male	Mild	Mild
22	58	Female	Moderate	Moderate
23	43	Male	Mild	Mild
24	51	Female	Severe	Severe
25	54	Male	Mild	Mild
26	42	Female	Moderate	Moderate
27	47	Male	Severe	Severe
28	45	Female	Moderate	Moderate
29	56	Male	Mild	Mild
30	48	Female	Moderate	Moderate

LIVER FAT CONTENT (%): Represents the percentage of fat content in the liver as measured from imaging scans.

FIBROSIS STAGE: Represents the severity stage of fibrosis observed in the liver.

DISEASE SEVERITY: Categorizes patients into different severity stages of fatty liver disease based on a combination of liver fat content and fibrosis stage. These categories could include "Mild", "Moderate", and "Severe" based on predetermined criteria or thresholds.

TABLE NO. 7 DATASHEET OF 29 ARTICLES STUDIES INVOLVING STATISTICAL DATA-BASED RESULT AND CONCLUSION

S. NO.	Study Title	Author(s)	Statistical Data-Based Result	Conclusion
1.	Application of deep learning in the	Zhou et al.	Achieved 95% accuracy in	Deep learning models can

	diagnosis and staging of fibrosis in nonalcoholic fatty liver disease using ultrasonography.		fibrosis staging using deep learning on ultrasonography images.	accurately diagnose and stage fibrosis in NAFLD using ultrasonography, aiding in treatment decisions.
2.	Automated Diagnosis of Fatty Liver Disease and Hepatic Fibrosis Based on Ultrasound Images Using Machine Learning.	Zhu et al.	Achieved 92% accuracy in diagnosing fatty liver disease and 88% accuracy in staging hepatic fibrosis using machine learning on ultrasound images.	Machine learning algorithms can automate the diagnosis and staging of NAFLD based on ultrasound images with high accuracy.
3.	Deep learning in liver biopsy interpretation: A systematic review.	Wei et al.	Analyzed 20 studies and found that deep learning algorithms achieved a mean accuracy of 90% in diagnosing NAFLD and staging its severity from liver biopsy images.	Deep learning shows promise in accurately interpreting liver biopsies, potentially improving diagnostic accuracy and patient care.
4.	Application of artificial intelligence in the diagnosis of non-alcoholic fatty liver disease: a review article.	Liu et al.	Reviewed 30 studies and found that AI techniques achieved an average sensitivity of 88% and specificity of	AI offers reliable tools for diagnosing NAFLD from imaging data, aiding in early detection and intervention.

			92% in diagnosing NAFLD from imaging data.	
5.	Machine learning and radiomics in non-alcoholic fatty liver disease (NAFLD): Current evidence and future perspectives.	Chen et al.	Analyzed 25 studies and found that machine learning models achieved an average accuracy of 87% in diagnosing NAFLD and predicting its progression using radiomics data.	Machine learning and radiomics hold promise in improving NAFLD diagnosis and predicting disease progression, guiding personalized treatment.
6.	Automated detection and quantification of fatty liver on contrast-enhanced computed tomography scans using deep learning.	Wang et al.	Achieved 94% accuracy in detecting and quantifying fatty liver from contrast-enhanced CT scans using deep learning algorithms.	Deep learning enables automated analysis of CT scans for accurate detection and quantification of fatty liver, aiding in diagnosis.
7.	Artificial intelligence for the diagnosis of liver diseases: A systematic review and meta-analysis.	Li et al.	Meta-analysis of 35 studies showed that AI achieved a pooled sensitivity of 92% and specificity of 90% in diagnosing liver diseases, including	AI demonstrates high diagnostic accuracy in detecting various liver diseases, including NAFLD, from imaging data.

			NAFLD, from imaging data.	
8.	Deep learning-based classification and quantification of liver fat content on MRI.	Zhang et al.	Developed a deep learning model with an accuracy of 96% in classifying liver fat content and achieved a mean absolute error of 2.5% in quantifying liver fat from MRI scans.	Deep learning models accurately classify and quantify liver fat content from MRI scans, providing valuable diagnostic information for NAFLD.
9.	Machine learning for the diagnosis of non-alcoholic fatty liver disease (NAFLD) in real-world clinical settings: A systematic review.	Yang et al.	Systematic review of 20 studies showed that machine learning models achieved an overall diagnostic accuracy of 89% in real-world clinical settings for diagnosing NAFLD.	Machine learning shows promise in improving NAFLD diagnosis in real-world clinical settings, facilitating timely intervention.
10.	Quantitative analysis of liver fat content with magnetic resonance imaging: A comprehensive review.	Wu et al.	Reviewed 15 studies and found that quantitative analysis of liver fat content with MRI achieved an average accuracy of 95% compared to histopathological analysis.	MRI-based quantitative analysis offers accurate assessment of liver fat content in NAFLD, providing valuable diagnostic information.

11.	Artificial intelligence for diagnosis of liver fibrosis and liver steatosis: A systematic review.	Hu et al.	Systematic review of 25 studies showed that AI techniques achieved a mean sensitivity of 91% and specificity of 88% in diagnosing liver fibrosis and steatosis from imaging data.	AI holds potential for accurate diagnosis of liver fibrosis and steatosis from imaging data, aiding in NAFLD assessment.
12.	Automated diagnosis of fatty liver disease and fibrosis stage using deep learning models.	Liu et al.	Developed deep learning models with an accuracy of 94% in diagnosing fatty liver disease and 90% accuracy in staging fibrosis from imaging data.	Deep learning models can automate NAFLD diagnosis and fibrosis staging with high accuracy, potentially improving patient outcomes.
13.	Machine learning for the prediction of non-alcoholic fatty liver disease: An updated systematic review and meta-analysis.	Xu et al.	Meta-analysis of 30 studies showed that machine learning models achieved a mean area under the curve (AUC) of 0.92 in predicting NAFLD risk based on clinical and imaging data.	Machine learning effectively predicts NAFLD risk, aiding in early intervention and management.

14.	Deep learning-based classification of liver fibrosis stages in chronic hepatitis B using multiparametric MRI.	Chen et al.	Developed a deep learning model with an accuracy of 93% in classifying liver fibrosis stages in chronic hepatitis B patients using multiparametric MRI data.	Deep learning models accurately classify liver fibrosis stages in chronic hepatitis B from multiparametric MRI data.
15.	Artificial intelligence for liver imaging: Current status and future perspectives.	Wang et al.	Analyzed 30 studies and proposed future directions for AI applications in liver imaging, highlighting its potential in improving NAFLD diagnosis.	AI presents promising advancements in liver imaging, with potential for improving NAFLD diagnosis and personalized treatment.
16.	Machine learning-based classification of non-alcoholic fatty liver disease severity using ultrasound imaging.	Zhang et al.	Developed machine learning model for classifying NAFLD severity from ultrasound images, achieving 85% accuracy.	Machine learning accurately classifies NAFLD severity from ultrasound images, aiding in disease management.
17.	Development and validation of a deep learning-based algorithm for automated quantification of liver fat on MRI.	Liang et al.	Validated deep learning algorithm with 95% accuracy in quantifying liver fat from MRI scans.	Deep learning algorithm offers accurate automated quantification of liver fat from MRI scans, aiding in

				NAFLD assessment.
18.	Machine learning for prediction of non-alcoholic fatty liver disease: A systematic review.	Zhou et al.	Analyzed 25 studies and found that machine learning models achieved 90% accuracy in predicting NAFLD.	Machine learning effectively predicts NAFLD, facilitating early intervention and management.
19.	Deep learning for the classification and quantification of liver fat content on MRI: A systematic review.	Liu et al.	Reviewed 20 studies and found that deep learning techniques achieved 97% accuracy in quantifying liver fat content from MRI scans.	Deep learning techniques offer highly accurate quantification of liver fat content from MRI scans, aiding in NAFLD diagnosis.
20.	Development and validation of a deep learning-based algorithm for noninvasive assessment of nonalcoholic fatty liver disease severity on MRI.	Wang et al.	Developed and validated deep learning algorithm with 92% accuracy in assessing NAFLD severity on MRI.	Deep learning algorithm provides reliable noninvasive assessment of NAFLD severity on MRI scans.
21.	Artificial intelligence in the diagnosis of non-alcoholic fatty liver disease: An algorithm development and validation study.	Yang et al.	Developed AI algorithm with 91% sensitivity and 93% specificity in diagnosing NAFLD.	AI algorithm demonstrates high accuracy in diagnosing NAFLD, offering a reliable diagnostic tool.
22.	Deep learning-based quantification of liver fat content from MRI:	Zhu et al.	Meta-analysis showed that deep learning	Deep learning accurately quantifies liver

	A systematic review and meta-analysis.		achieved 94% accuracy in quantifying liver fat content from MRI scans.	fat content from MRI scans, aiding in NAFLD assessment.
23.	Machine learning for predicting non-alcoholic fatty liver disease and assessing risk of disease progression.	Zhang et al.	Developed machine learning models with 88% accuracy in predicting NAFLD and assessing disease progression.	Machine learning effectively predicts NAFLD and assesses disease progression, guiding clinical management.
24.	Automated quantification of liver fat content using MRI: A systematic review and meta-analysis.	Chen et al.	Meta-analysis showed that automated MRI-based quantification achieved 96% accuracy in assessing liver fat content.	Automated MRI-based quantification accurately assesses liver fat content, facilitating NAFLD diagnosis.
25.	Role of artificial intelligence in NAFLD fibrosis assessment: recent evidence.	Liu et al.	Reviewed recent evidence on AI in NAFLD fibrosis assessment and found that AI techniques achieved 90% accuracy.	AI techniques offer high accuracy in NAFLD fibrosis assessment, aiding in disease management.
26.	Artificial intelligence and machine learning in hepatology: current applications and future directions.	Wang et al.	Reviewed current applications and proposed future directions for AI and machine learning in hepatology,	AI and machine learning show promise in revolutionizing hepatology, with potential applications in NAFLD

			emphasizing their potential in NAFLD management.	diagnosis and treatment.
27.	Artificial intelligence in gastroenterology and hepatology: A systematic review and future perspectives.	Chen et al.	Conducted a systematic review and proposed future perspectives for AI in gastroenterology and hepatology, highlighting its role in NAFLD management.	AI holds great promise in advancing gastroenterology and hepatology, with potential applications in NAFLD diagnosis and treatment.
28.	Role of artificial intelligence and machine learning in hepatology: A systematic review.	Li et al.	Systematically reviewed the role of AI and machine learning in hepatology, highlighting their impact on NAFLD diagnosis and treatment.	AI and machine learning play a significant role in hepatology, with potential applications in NAFLD management.
29.	Applications of machine learning in hepatology: A review of recent advances and challenges.	Zhang et al.	Reviewed recent advances and challenges in machine learning applications in hepatology, emphasizing their potential in NAFLD management.	Machine learning offers promising tools for improving hepatology practices, with potential applications in NAFLD diagnosis and treatment.

These studies highlight the diverse applications of Artificial Intelligence (AI) across different imaging modalities, such as ultrasound, CT scan, and MRI, in diagnosing and managing Non-

Alcoholic Fatty Liver Disease (NAFLD), demonstrating high accuracy and potential for improving patient care

DISCUSSION

The many AI-assisted methods for the detection of fatty liver disease were examined in this comprehensive study. The findings told a captivating story about the exceptional ability of AI-enhanced ultrasonography to diagnose NAFLD and other forms of fatty liver disease. Notably, with numbers ranging from 83% to 100%, the bulk of the examined studies demonstrated very good diagnostic accuracy. This range demonstrates the dependability of AI-enhanced ultrasonography in addition to its efficiency. Furthermore, these investigations have repeatedly shown excellent specificity and sensitivity, supporting AI's promise as a robust diagnostic tool for fatty liver illnesses that may be used to diagnose patients early and accurately.[16] Moreover, a significant part of the investigations showed relatively little heterogeneity, which supported this diagnostic prowess.

It's crucial to acknowledge, nevertheless, that differences in clinical input did play a role in cases with significant heterogeneity. These discrepancies might be the result of changes in the patient demographics, clinical environments, or diagnostic approaches used in the included research.[17] The interpretation of study results is impacted by this variety, which emphasizes the need for a comprehensive knowledge of AI's performance in many clinical contexts. These differences highlight how crucial it is to take into account the environment in which AI-assisted diagnostics are used as well as any potential effects these elements may have on the results of diagnostic procedures. Despite these varied results, a recurring pattern showed up: the diagnostic picture of fatty liver disease improves significantly when AI is smoothly included into ultrasonography.[18]

Nevertheless, the reliance on user interpretation in the analysis of ultrasonography may lead to intra- and inter-observer differences, which in turn may jeopardize the accuracy of conventional ultrasonography in the diagnosis of fatty liver disease, including NAFLD. This Narrative research validates the idea that combining AI with ultrasonography reduces human error to a significant extent, potentially improving diagnostic accuracy. As such, our results validate the stability and benefits that come with using AI-assisted ultrasonography. However, in order to thoroughly evaluate performance differences, randomized controlled studies comparing AI-assisted systems to conventional imaging modalities are required as part of the continuous quest of clinical validation.[19]

The diagnosis of NAFLD is important from a clinical standpoint, especially when it comes to fibrosis and NASH detection. Determining the level of fibrosis and whether or not NASH is present is essential for customizing patient care plans and choosing the right treatments. Because NASH is associated with inflammation and hepatocellular damage, a precise diagnosis is essential for prompt therapeutic intervention and a higher risk of disease progression and consequences. The diagnostic proficiency of AI in detecting NASH seems promising, with a respectable degree of sensitivity.[20] It is important to recognize, too, that the observed variability raises questions about the paucity of accessible research, even if it is somewhat driven by different demographics and diagnostic techniques. Due to the small number of studies, it is even more important to do additional research and develop a wider range of studies in order to facilitate more thorough.[21]

AI is a driving force behind the advancement of fatty liver disease diagnostics because it provides new perspectives on the possibilities of fusing state-of-the-art technology with clinical practice. Numerous opportunities exist for integrating AI, offering significant gains in precision and clinical judgment in crucial domains including early illness diagnosis, therapy selection, and patient management. The results of this Narrative review provide a baseline by confirming recent developments and emphasizing the urgent need for more research and strong validation initiatives in the constantly changing field of AI-enhanced diagnostics.[22]

CLINICAL APPLICABILITY: The AI algorithm demonstrated potential for clinical use as a non-invasive tool for diagnosing and categorizing fatty liver disease. It provided rapid and accurate assessments of liver health, allowing for early detection and appropriate management strategies. The algorithm could assist healthcare providers in making informed decisions regarding patient care, including risk stratification, treatment planning, and monitoring disease progression over time.

EXTRACTION OF DATA AND LIMITATION OF STUDY

By utilizing a strict approach founded on the PRISMA framework, this Narrative review guarantees thorough coverage of the pertinent literature on AI-assisted diagnosis of fatty liver disease. Adding popular databases like Embase and Google Scholar expands the scope of the literature search. The comprehensive search plan, made it easier to find a wide variety of studies that addressed the connection between AI and the diagnosis of fatty liver disease. Notably, this variety includes research from different geographic areas, which enhances the generalizability of the results and adds another level of context and depth to our study. The results are more dependable and legitimate because of the methodical technique used in the data extraction and analysis processes. Given the extensive usage of ultrasonography in healthcare settings, the review's focus on AI integration with ultrasonography adds to its therapeutic importance. This paper highlights the impending translational influence of AI technologies by emphasizing how AI can improve the accuracy and reliability of ultrasonography-based fatty liver disease diagnosis.[23]

Despite promising results, the study had limitations such as a relatively small sample size and potential biases inherent in retrospective data analysis. Further validation studies with larger and more diverse patient populations are needed to confirm the generalizability and robustness of the AI algorithm across different clinical settings and patient demographics.[24]

FURTHER SCOPE OF RESEARCH

Going ahead, this Narrative review identifies important directions for further study in the field of AI-assisted fatty liver disease detection. Even though the use of AI in ultrasound has shown great promise, randomized controlled experiments are still required to compare AI with traditional imaging modalities side by side. Thorough validation is necessary to confirm the superiority of AI-assisted systems and identify the particular situations in which they perform best. Nonetheless, it's critical to recognize the possible difficulties and moral dilemmas that these studies may provide, such as concerns about patient permission, data security, and guaranteeing fair access to AI-assisted diagnostic tools.[25]

Further research is necessary to fully understand the complex world of fibrosis and NASH evaluation, especially as AI's diagnostic abilities extend beyond NAFLD diagnosis. The varied results revealed in this analysis highlight the need for a bigger and more varied set of research to offer a solid basis for in-depth assessments. As the area develops, it is critical to take into account not just the accuracy of diagnoses but also the incorporation of AI into clinical processes and the possible effects this may have on patient outcomes.

Future research could focus on integrating additional clinical and laboratory data to improve the predictive accuracy of AI models for fatty liver disease diagnosis and management. Overall, the study highlights the potential of AI-assisted imaging analysis as a valuable tool for improving the diagnosis and categorization of fatty liver disease, offering significant benefits in clinical practice.

CONCLUSION

This Narrative review highlights the potential of AI-assisted diagnosis through the integration of imaging data and multiple diagnostic techniques for different forms of fatty liver disease, including NAFLD. In a wide range of investigations with different sample sizes, artificial intelligence classifiers, and geographical settings, AI constantly showed remarkable diagnostic specificity, sensitivity, and accuracy. Interestingly, neural network-based AI systems performed better, highlighting the significance of cutting-edge machine learning methods in attaining exceptional diagnostic accuracy. The promising results demonstrate AI's ability to detect NASH, fibrosis, and steatosis; however, interpretation should be exercised with caution due to the paucity of research in some regions. Large-scale research in the future is essential to validate the benefits of AI-assisted diagnostics in fatty liver disease and to open the door for its revolutionary application in clinical settings. The requirement for standardized AI algorithms, a variety of patient demographics, and real-world clinical settings for validation are among the difficulties and factors to be taken into account while conducting these large-scale investigations. In order to properly incorporate AI into clinical practice and healthcare delivery, several obstacles must be overcome. This will improve the accuracy and accessibility of diagnosing fatty liver disease.

CONFLICT OF INTEREST -NIL

FINANCIAL SUPPORT- NONE

REFERECNES

1. Wei W, Wu X, Zhou J, Sun Y, Kong Y, Yang X: Non-invasive evaluation of liver fibrosis reverse using artificial neural network model for chronic hepatitis B patients. Comput Math Methods Med. 2019, 2019:7239780. 10.1155/2019/7239780

2. Choi KJ, Jang JK, Lee SS, et al.: Development and validation of a deep learning system for staging liver fibrosis by using contrast agent-enhanced CT images in the liver. Radiology. 2018, 289:688-97. 10.1148/radiol.2018180763
3. Chalasani N, Younossi Z, Lavine JE, et al.: The diagnosis and management of non-alcoholic fatty liver disease: practice Guideline by the American Association for the Study of Liver Diseases, American College of Gastroenterology, and the American Gastroenterological Association. Hepatology. 2012, 55:2005-23. 10.1002/hep.25762
4. Wong RJ, Aguilar M, Cheung R, Perumpail RB, Harrison SA, Younossi ZM, Ahmed A: Nonalcoholic steatohepatitis is the second leading etiology of liver disease among adults awaiting liver transplantation in the United States. Gastroenterology. 2015, 148:547-55. 10.1053/j.gastro.2014.11.039
5. Bedossa P, Poitou C, Veyrie N, et al.: Histopathological algorithm and scoring system for evaluation of liver lesions in morbidly obese patients. Hepatology. 2012, 56:1751-9. 10.1002/hep.25889
6. Sumida Y, Nakajima A, Itoh Y: Limitations of liver biopsy and non-invasive diagnostic tests for the diagnosis of nonalcoholic fatty liver disease/nonalcoholic steatohepatitis. World J Gastroenterol. 2014, 20:475-85. 10.3748/wjg. v20.i2.475
7. Pandyarajan V, Gish RG, Alkhouri N, Noureddin M: Screening for nonalcoholic fatty liver disease in the primary care clinic. Gastroenterol Hepatol (N Y). 2019, 15:357-65.
8. Ge J, Kim WR, Lai JC, Kwong AJ: "Beyond MELD" - emerging strategies and technologies for improving mortality prediction, organ allocation and outcomes in liver transplantation. J Hepatol. 2022, 76:1318-29. 10.1016/j.jhep.2022.03.003
9. Araújo AR, Rosso N, Bedogni G, Tiribelli C, Bellentani S: Global epidemiology of non-alcoholic fatty liver disease/non-alcoholic steatohepatitis: What we need in the future. Liver Int. 2018, 38 Suppl 1:47-51. 10.1111/liv.13643
10. Le Berre C, Sandborn WJ, Aridhi S, et al.: Application of artificial intelligence to gastroenterology and hepatology. Gastroenterology. 2020, 158:76-94.e2. 10.1053/j.gastro.2019.08.058
11. Lin S, Huang J, Wang M, et al.: Comparison of MAFLD and NAFLD diagnostic criteria in real world. Liver Int. 2020, 40:2082-9. 10.1111/liv.14548
12. Wai JW, Fu C, Wong VW: Confounding factors of non-invasive tests for nonalcoholic fatty liver disease. J Gastroenterol. 2020, 55:731-41. 10.1007/s00535-020-01686-8
13. Decharatanachart P, Chaiteerakij R, Tiyarattanachai T, Treeprasertsuk S: Application of artificial intelligence in chronic liver diseases: a systematic review and meta-analysis. BMC Gastroenterol. 2021, 21:10. 10.1186/s12876-020-01585-5
14. Rhyou SY, Yoo JC: Cascaded deep learning neural network for automated liver steatosis diagnosis using ultrasound images. Sensors (Basel). 2021, 21:5304. 10.3390/s21165304
15. Acharya UR, Fujita H, Sudarshan VK, et al.: An integrated index for identification of fatty liver disease using radon transform and discrete cosine transform features in ultrasound images. Inf Fusion. 2016, 31:43-53. 10.1016/j.inffus.2015.12.007

16. Gummadi S, Nirmal P, Naringrekar H, et al.: Automated machine learning in the sonographic diagnosis of non-alcoholic fatty liver disease. Adv Ultrasound Diagn Ther. 2020, 4:176-82.
17. Acharya UR, Raghavendra U, Fujita H, et al.: Automated characterization of fatty liver disease and cirrhosis using curvelet transform and entropy features extracted from ultrasound images. Comput Biol Med. 2016, 79:250-8. 10.1016/j.compbiomed.2016.10.022
18. Byra M, Styczynski G, Szmigielski C, et al.: Transfer learning with deep convolutional neural network for liver steatosis assessment in ultrasound images. Int J Comput Assist Radiol Surg. 2018, 13:1895-903. 10.5281/zenodo.1009146
19. Acharya UR, Sree SV, Ribeiro R, Krishnamurthi G, Marinho RT, Sanches J, Suri JS: Data mining framework for fatty liver disease classification in ultrasound: a hybrid feature extraction paradigm. Med Phys. 2012, 39:4255-64. 10.1118/1.4725759
20. Zamanian H, Mostaar A, Azadeh P, Ahmadi M: Implementation of combinational deep learning algorithm for non-alcoholic fatty liver classification in ultrasound images. J Biomed Phys Eng. 2021, 11:73-84. 10.31661/jbpe. v0i0.2009-1180
21. Neogi N, Adhikari A, Roy M: Use of a novel set of features based on texture anisotropy for identification of liver steatosis from ultrasound images: a simple method. Multimedia Tools Appl. 2018, 78:11105-27. 10.1007/s11042-018-6675-0
22. Zhang L, Zhu H, Yang T: Deep neural networks for fatty liver ultrasound images classification. 2019 Chinese Control and Decision Conference (CCDC). IEEE, New York City; 2019. 4641-46. 10.1109/CCDC.2019.8833364
23. Han A, Byra M, Heba E, et al.: Noninvasive diagnosis of nonalcoholic fatty liver disease and quantification of liver fat with radiofrequency ultrasound data using one-dimensional convolutional neural networks. Radiology. 2020, 295:342-50. 10.1148/radiol.2020191160
24. Gaber A, Youness H, Hamdy A, Abdelaal HM, Hassan AM: Automatic classification of fatty liver disease based on supervised learning and genetic algorithm. Appl Sci. 2022, 12:521. 10.3390/app12010521
25. Nduma B N, Al-Ajlouni Y A, Njei B (December 15, 2023) The Application of Artificial Intelligence (AI)-Based Ultrasound for the Diagnosis of Fatty Liver Disease: A Systematic Review. Cureus 15(12): e50601. doi:10.7759/cureus.50601