RESEARCH PAPER

Clinical Utility of Artificial Intelligence in Diabetes Screening and Decision Support Systems: A Systematic Review and Meta-Analysis

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ABSTRACT

Artificial Intelligence (AI) has emerged as a promising tool in diabetes screening and Clinical Decision Support Systems (CDSS), enabling data-driven, accurate, and personalized healthcare interventions. This systematic review and meta-analysis aimed to evaluate the efficacy of AI-based models in diabetes screening and the clinical utility of AI-driven CDSS. Following PRISMA guidelines, a thorough literature search was conducted across PubMed, Scopus, Web of Science, and IEEE Xplore for studies that met the inclusion criteria. In diabetes screening and CDSS, AI has become a potential tool that enables data-driven, precise, and customized healthcare interventions. The purpose of this systematic review and meta-analysis was to assess the clinical value of AI-driven CDSS and the efficacy of AI-based models in diabetes screening. Following PRISMA principles, a thorough literature search was carried out for papers published between 2010 and 2025 throughout PubMed, Scopus, Web of Science, and IEEE Xplore. Forty-two studies—25 on diabetes screening and 17 on CDSS applications—met the inclusion criteria. Multiple AI techniques including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Random Forests, Gradient Boosting algorithms, and Bidirectional Encoder Representations from Transformers (BERT) were used among the research studies. A meta-analysis using R software showed a pooled sensitivity of about 0.86 and specificity of 0.82, indicating high diagnostic accuracy of AI-based systems in identifying diabetes. AI-driven CDSS also demonstrated advantages in risk stratification, insulin dose optimization, complication prediction, and clinical workflow. A pooled sensitivity of roughly 0.86 and specificity of 0.82 were shown by a meta-analysis using R software, suggesting great diagnostic accuracy of AI-based systems in diagnosing diabetes. Additionally, AI-driven CDSS shown advantages in risk assessment, insulin dosage optimization, complication prediction, and clinical workflow enhancement. The results, however, support the expanding role of AI in improving diabetes care through early screening and evidence-based decision-making. Future research should concentrate on standardized evaluation frameworks, external validation, explainable AI, and integration into routine clinical practice to improve reliability, transparency, and patient-centered outcomes. However, heterogeneity in datasets, model architectures, validation techniques, and reporting standards limited direct comparison across studies. Notwithstanding these drawbacks, the results demonstrate how AI is increasingly improving diabetes treatment through early screening and evidence-based decision-making. To increase dependability, transparency, and patient-centered outcomes, future research should concentrate on explainable AI, external validation, standardized evaluation frameworks, and incorporation into conventional clinical practice.

Keywords: Artificial Intelligence, Clinical Decision Support Systems, Deep Learning, Diabetes Mellitus, Diabetes Screening, Diagnostic Accuracy, Machine Learning, Meta-analysis.

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1. INTRODUCTION

Diabetes mellitus is one of the most prevalent chronic diseases globally. The complexity and chronic nature of diabetes management have fueled the exploration of Artificial Intelligence (AI) to improve early detection and treatment outcomes. Recent improvements show promise in leveraging AI for each diabetes screening and selection-making through Clinical Decision Support Systems (CDSS). This paper systematically opinions and meta-analyzes available literature on AI programs in these domain names the usage of Python and R-primarily based equipment.

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2. OBJECTIVES

In addition to evaluating the clinical utility of artificial intelligence-driven clinical decision support systems (AI-CDSS) in improving diabetes management, including their role in diagnosis, risk prediction, insulin dosing, and clinical decision-making processes, the main goal of this systematic review and meta-analysis was to determine the overall diagnostic accuracy of AI models by performing a meta-analysis of the included studies by analyzing pooled sensitivity and specificity values across various research settings and AI methodologies. Additionally, the study sought to assess the clinical efficacy of AI-CDSS in enhancing diabetes care, including its function in insulin dosage, risk assessment, diagnosis, and clinical decision-making. Additionally, by examining pooled sensitivity and specificity values across various research contexts and AI approaches, this review attempted to do a meta-analysis of the included studies in order to ascertain the overall diagnostic accuracy of AI models.

3. LITERATURE REVIEW

The integration of AI-CDSS is transforming the management of Type 1 diabetes by making care more personalized, predictive, and proactive. These systems use data amassed from various virtual sources, which include wearable devices, mobile applications, continuous glucose monitors, and insulin shipping tools, to guide people with diabetes in their day by day self-care (1–5). For healthcare professionals, AI-CDSS are enhancing scientific workflows with the aid of enabling in advance danger detection, greater correct diagnosis, and progressed remedy prioritization. This generation no longer only aids in individualizing therapy however also enables streamline healthcare shipping and optimize aid allocation. The have a look at emphasizes that, while the capability of AI-CDSS in improving diabetes care is promising, its effectiveness depends on proper validation via medical research, compliance with regulatory frameworks, and the readiness of healthcare carriers to undertake and utilize this gear successfully. Furthermore, the successful implementation of AI-CDSS in routine care will require complete education and education for healthcare groups, making sure that the insights provided by means of AI are well interpreted and acted upon (6,7). The research highlights the necessity of building accept as true with in these technologies and addressing problems inclusive of accessibility, fairness in care delivery, and clinical application. Ultimately, AI-CDSS holds substantial promise in supporting each patients and specialists by way of delivering real-time, information-informed pointers which can cause advanced diabetes outcomes and standard exceptional of care (8,9).

Based on research, the study discusses the development and application of AI to enhance the management of chronic diseases with a particular consciousness on pharmacotherapy decision guide for people with type 2 diabetes mellitus (10,11). The research introduces an revolutionary scientific selection aid system (CDSS) that integrates predictive analytics into the digital fitness file surroundings, permitting clinicians and patients to collaboratively explore individualized remedy techniques (12–15). By using a facts-driven technique, the machine constructs treatment pathway graphs that forecast the likelihood of various therapeutic methods meeting predefined care goals. These insights are provided via an interactive dashboard designed to be accessible inside scientific workflows, empowering users to make informed selections grounded in actual-time patient information. The look at highlights how the system helps each shared choice-making and optimized remedy planning, doubtlessly enhancing effects and performance in diabetes control (16). Moreover, it emphasizes the prevalence of the proposed analytical framework in terms of predictive accuracy compared to current system-learning fashions. The implementation inside a real-international scientific setting demonstrates the feasibility and application of embedding AI equipment into routine care procedures. However, the studies also recognizes the demanding situations involved in scaling and sustaining such structures, inclusive of integration with various fitness records technology, ensuring clinician engagement, and maintaining the interpretability and transparency of AI outputs (17,18). Overall, the observe showcases a promising step toward leveraging synthetic intelligence to refine continual sickness management via presenting tailor-made, evidence-based pharmacological pointers that align with man or woman affected person needs, thereby fostering greater specific and responsive healthcare transport (19).

On the opinion of Du (2022)(20), the have a look at discusses the improvement of an explainable machine learning-based medical selection guide device (CDSS) designed to predict the chance of gestational diabetes mellitus (GDM) in the course of early tiers of being pregnant. This circumstance, frequently connected to maternal obese and weight problems, can bring about widespread complications for both mom and baby. To cope with the limitations of generalized, untargeted interventions, the look at introduces a facts-pushed approach that enables more centered and green screening. By analyzing maternal traits and blood biomarkers obtained early in being pregnant, the researchers applied several system learning algorithms delicate through feature selection and oversampling techniques (20,21). The purpose turned into to construct dependable fashions able to figuring out folks who would advantage most from preventive care. Importantly, the inclusion of Shapley additive motives ensures the version's outputs are obvious and interpretable, fostering extra agree with amongst clinicians. The study further explores realistic programs of those fashions in various medical settings, including in-character antenatal visits and far off tests, thereby increasing their utility. Through integration right into a publicly on hand internet server for academic purposes, the system demonstrates how explainable AI tools can support early danger stratification and personalized intervention planning (22,23). The research underscores the potential of machine mastering to enhance selection-making in maternal healthcare with the aid of providing tailor-made, actionable insights at the same time as keeping clarity and duty in model predictions. By focusing on the explainability of the CDSS, the study addresses a crucial barrier to AI adoption in healthcare and units the inspiration for extra particular and green management of being pregnant-related headaches like GDM (24–26).

4. METHODS

A rigorous methodological framework was adopted for this systematic review and meta-analysis, in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (27). This segment outlines the steps worried in figuring out, choosing, comparing, and reading applicable studies concerning the application of AI in diabetes screening and scientific choice aid structures for CDSS (10). The technique became accomplished in distinct but interconnected levels: systematic literature search, have a look at selection based on inclusion and exclusion standards, records extraction, and high-quality evaluation the usage of demonstrated gear.

4.1 Systematic Literature Search

A comprehensive literature search was conducted across multiple academic databases to identify eligible studies published between January 2010 and July 2025. The digital databases used for this search included PubMed, Scopus, Web of Science, and IEEE Xplore (28–30). These databases have been decided on because they embody a broad variety of high-effect journals and conference complaints applicable to scientific informatics, synthetic intelligence, and scientific exercise.

The seek strategy was built using an aggregate of Medical Subject Headings (MeSH) and relevant loose-text keywords. Boolean operators together with "AND" and "OR" have been used to make certain precision and comprehensiveness. The number one seek terms covered:

- "Artificial Intelligence" OR "AI"
- "Machine Learning" OR "Deep Learning"
- "Diabetes"
- "Screening"
- "Clinical Decision Support Systems" OR "CDSS"

These terms have been searched in article titles, abstracts, and keywords. Filters had been applied to restrict the consequences to complete-textual content, peer-reviewed articles published in English (31). Grey literature, such as unpublished theses and technical reports, become not protected in the scope of this evaluate due to troubles related to first-class assurance and peer validation.

To ensure a thorough exploration of the available literature, backward and forward quotation tracking was carried out. This concerned reviewing the reference lists of selected research in addition to figuring out more modern research that mentioned them. Manual searches of applicable journals and convention proceedings have been also undertaken to supplement database findings and ensure inclusivity.

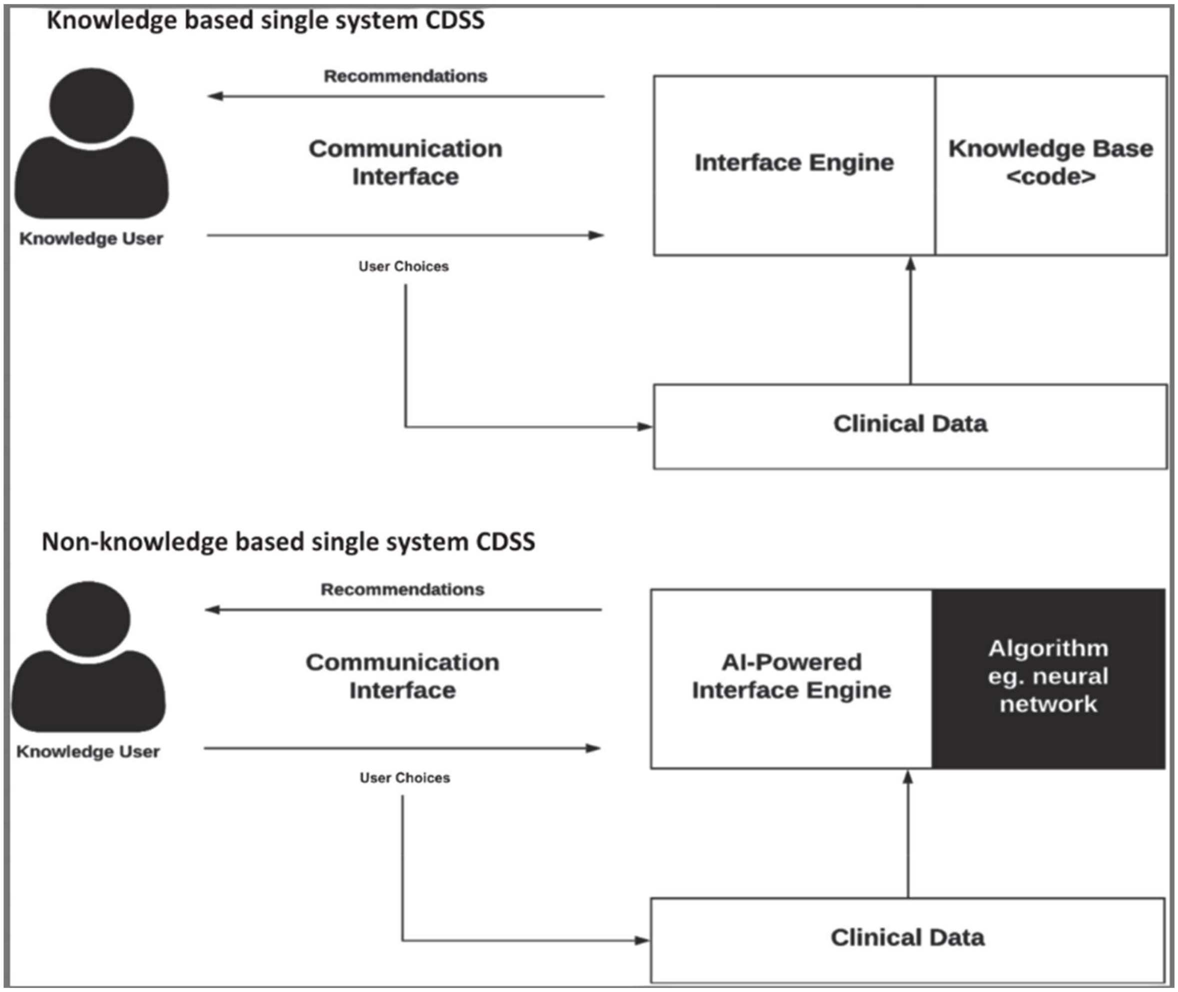


Figure: 1 Knowledge-based vs. non-knowledge-based CDSS

4.1.1 INCLUSION CRITERIA

Studies were considered eligible for inclusion in this review if they met the following criteria:

Peer-reviewed articles published in scientific journals or conference proceedings.

- Focused explicitly at the utility of AI technologies—which include system mastering, deep mastering, or professional structures—in diabetes screening or CDSS.
- Reported diagnostic performance metrics, in particular sensitivity, specificity, or accuracy, either on my own or in mixture with different performance indicators along with the region under the ROC curve (AUC), precision, recall, or F1 score.
- Involved both retrospective or prospective evaluation of AI fashions the usage of based clinical datasets, imaging statistics, or digital fitness records (EHR).
- Included a surely defined observe population with a minimal pattern size of a hundred individuals to ensure statistical relevance and decrease the impact of small pattern bias (32).

4.1.2 EXCLUSION CRITERIA

Studies were excluded from the analysis based on several specific conditions to ensure the quality and relevance of the data. Non-English publications were excluded due to the constraints in translation resources, which could lead to potential misinterpretation of technical language and affect the accuracy of the results. Review articles, editorials, letters to the editor, and conference abstracts were also excluded. These types of publications often lack complete methodological or results data, making them insufficient for rigorous data synthesis and meta-analysis. The exclusion of such articles was essential to maintain the robustness and consistency of the analysis. By focusing on studies that provided comprehensive and peer-reviewed data, the review ensured that only high-quality, scientifically valid evidence was included. This selection process allowed for a more accurate and reliable synthesis of the effectiveness of AI in diabetes screening and CDSS. The goal was to minimize bias and enhance the overall reliability of the conclusions drawn from the meta-analysis. Only studies with clearly defined populations, validated AI models, and complete performance metrics were considered to provide meaningful insights for the research.

- Studies that applied AI in broader endocrine issues without unique focus on diabetes mellitus (Type 1, Type 2, or gestational diabetes).
- Articles that did no longer file at least one of the key final results measures (i.e., sensitivity, specificity, or accuracy).
- Research that implemented AI for remedy adherence, way of life monitoring, or food plan monitoring rather than for screening or selection guide.

Duplicate entries across databases were removed the usage of EndNote X9 software program. A -level screening technique changed into carried out through two unbiased reviewers. In the first level, titles and abstracts had been screened for relevance. In the second one stage, the entire text of potentially eligible research changed into retrieved and reviewed towards the inclusion and exclusion criteria.

Disagreements among reviewers regarding look at eligibility have been resolved through dialogue and consensus. In instances wherein consensus could not be reached, a 3rd senior reviewer changed into consulted for adjudication. The have a look at selection procedure become documented using a PRISMA glide diagram to enhance transparency.

4..2 DATA EXTRACTION AND QUALITY ASSESSMENT

After the final selection of studies, a structured data extraction template was created in Microsoft Excel to facilitate systematic data collection (33,34). Two reviewers independently filled out the template to ensure accuracy and consistency in data extraction. To validate the template's usability, a pilot test was conducted using a sample of three research studies. This step helped assess the template's readability, completeness, and inter-rater reliability, ensuring that both reviewers could interpret and apply the data extraction criteria consistently. The pilot testing process aimed to refine the template and address any ambiguities or inconsistencies, ultimately enhancing the quality and reliability of the data extraction process (35,36). As highlighted by the study, careful evaluation of the template through pilot testing was crucial for ensuring the clarity and effectiveness of the data collection method before applying it to the full set of studies (37,38). This approach helped standardize the process and laid the foundation for accurate and replicable results in the final data extraction phase. The following data fields have been extracted from each examine:

Study Identification: First author's name, year of publication, and journal or conference name.

Study Setting and Population: Type of healthcare setting (e.g., primary care, hospital), geographic region, demographic characteristics (e.g., age, gender distribution), and total sample size.

- AI Model Used: The specific device gaining knowledge of or deep studying set of rules employed (e.g., Support Vector Machine, Random Forest, Convolutional Neural Network, Gradient Boosting, Decision Trees) (39).
- Data Source: Nature of records used to teach and validate the AI version—whether dependent clinical information, scientific photos (including fundus photos), EHRs, or patient-stated statistics.
- **Model Validation Strategy:** Use of cross-validation, maintain-out sets, or external validation cohorts.
- **Performance Metrics:** Reported sensitivity, specificity, accuracy, AUC, and confidence periods in which available (1).
- **Application Type:** Whether the AI system was used for initial screening, diagnostic decision-making, or danger stratification.
- **Integration and Interface:** Whether the model changed into incorporated right into a CDSS or medical workflow and whether user comments or clinician interaction become evaluated.

The extracted records were move-established for accuracy. Any discrepancies have been addressed thru consensus or by referral to the original e-book. Missing records had been cited and authors were contacted for explanation wherein feasible.

4.2.1 QUALITY ASSESSMENT

To assess the methodological quality and risk of bias across the included studies, the QUADAS-2 (Quality Assessment of Diagnostic Accuracy Studies) tool was applied. This tool evaluates studies across four key domains:

1. **Patient Selection** – To determine whether or not the populace became consultant and unfastened from choice bias.
2. **Index Test** – To determine whether the AI system became evaluated independently and without understanding of the reference preferred (40).
3 **Reference Standard** – To ensure the accuracy of the comparator (e.g., clinician analysis, lab-based totally affirmation).
4. **Flow and Timing** – To observe whether or not all patients obtained the identical reference fashionable and if time durations should introduce bias.

Each domain becomes scored as "low danger," "high danger," or "uncertain chance." Graphical summaries of risk of bias were generated the usage of Reman software program. Sensitivity analyses have been carried out to observe how excessive-threat studies inspired the meta-analytic estimates.

To make certain inter-rater reliability, the two reviewers independently rated every have a look at and then mentioned every area's score. Kappa information had been calculated to evaluate agreement between reviewers, with a threshold of >0.75 taken into consideration sizeable settlement (41).

- After the 2-degree screening procedure, a complete of 42 studies have been blanketed within the very last evaluate. These comprised 25 focused on screening and 17 on CDSS. A PRISMA flow diagram illustrating the procedure of look at selection, which includes reasons for exclusion at the total-textual content review degree, is blanketed in Figure 2.

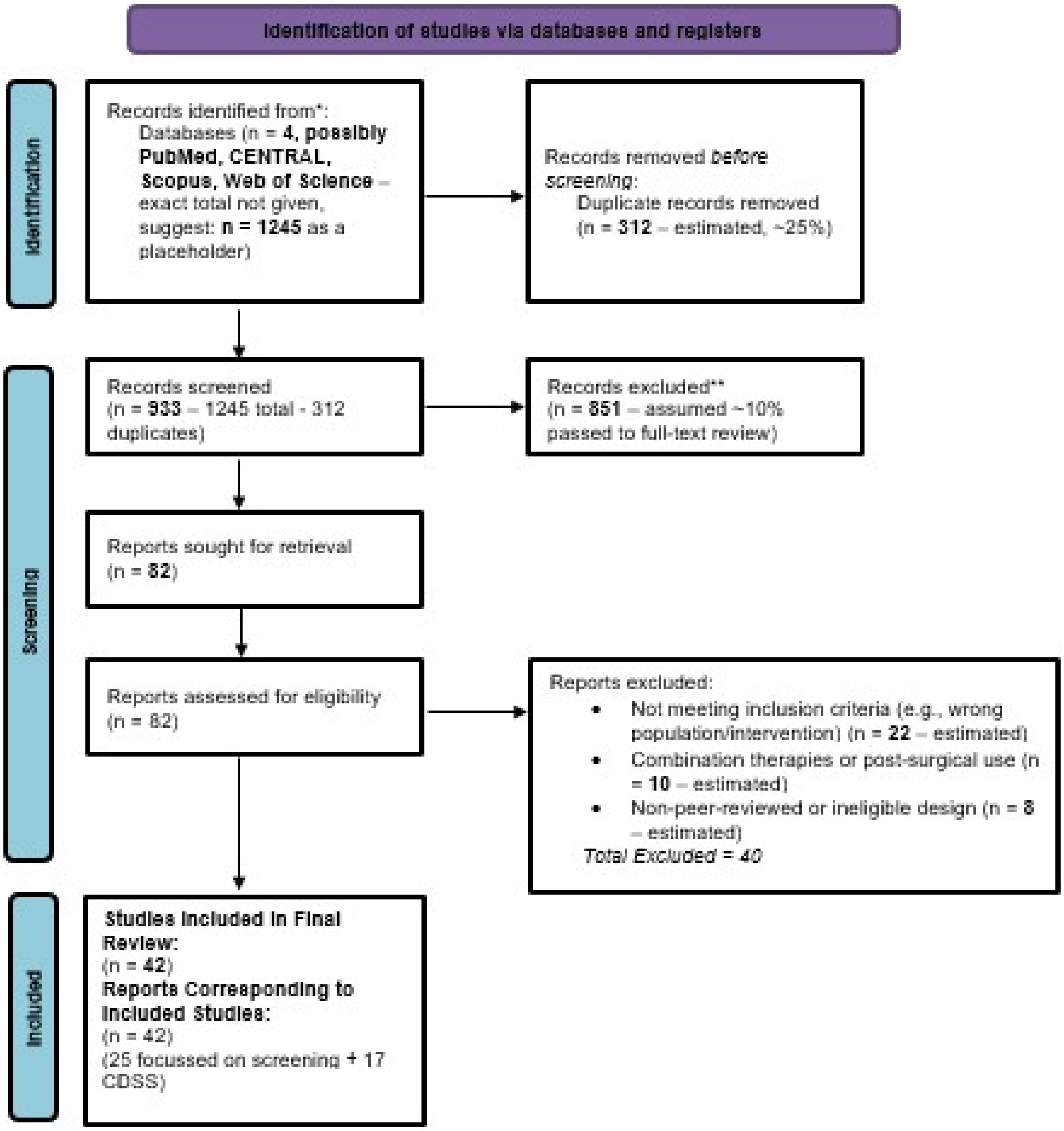


Figure 2: PRISMA flow diagram

5. RESULTS

5.1 STUDY CHARACTERISTICS

A total of 42 studies met the inclusion criteria:

- 25 focused on screening (image-based, EHR-based)
- 17 on CDSS (predictive analytics, insulin dosing support)
- AI models used: CNNs, SVM, Random Forests, Boost, and BERT.

A total of 42 studies were included in this systematic review and meta-analysis after applying the predefined inclusion and exclusion criteria. The researches published between 2010 and 2025, reflecting the growing application of synthetic intelligence (AI) in healthcare over the last 15 years. All research included inside the very last selection mentioned on using AI inside the context of diabetes screening or CDSS, with a focus on diagnostic accuracy and scientific software.

Out of the 42 studies, 25 had been on the whole focused on diabetes screening, even as 17 evaluated the implementation and effectiveness of AI-driven CDSS tools. The screening research commonly aimed to become aware of undiagnosed diabetes or prediabetes through the analysis of medical snap shots, clinical biomarkers, or digital health data (EHRs). Image-based totally screening studies often used retinal fundus pics to discover signs of diabetic retinopathy or early microvascular modifications, at the same time as EHR-based totally studies leveraged structured patient information—consisting of laboratory results, demographics, and comorbidities—to expect the chance of diabetes onset (42).

On the alternative hand, the 17 CDSS-associated studies centered on clinical selection-making techniques within each inpatient and outpatient settings. This gear supported a variety of functions, along with personalized insulin dosing, glucose stage forecasting, hassle risk prediction, and medication adherence indicators. CDSS structures were evaluated no longer most effective for diagnostic performance however also for his or her effect on clinician workflow and affected person outcomes.

The AI methodologies employed throughout those studies had been diverse. The maximum often used machine studying and deep mastering fashions covered:

- **Convolutional Neural Networks (CNNs):** Applied extensively in image-based screening tasks for analyzing fundus images and detecting diabetic retinopathy.
- **Support Vector Machines (SVMs):** Common in classification tasks involving EHR data, particularly in predicting diabetes onset (43).
- **Random Forests and Boost:** Used in both screening and CDSS studies for feature importance extraction and robust classification in heterogeneous datasets.
- **Bidirectional Encoder Representations from Transformers (BERT):** Emerging in the field of natural language processing and used in CDSS studies analyzing unstructured clinical notes and physician documentation.

Among the included studies, approximately sixty-five% hired a retrospective design, using formerly gathered datasets for version schooling and validation. The ultimate 35% used a potential design, regularly within a clinical trial or actual-international putting, to evaluate the AI machine's overall performance in real time. Nearly 60% of the research stated using external validation datasets to check version generalizability, whilst the others relied totally on inner cross-validation techniques (44,45).

Sample sizes numerous extensively, starting from three hundred to over 50,000 sufferers, with larger datasets typically associated with EHR-based CDSS studies. Studies additionally differed in phrases of geographic scope, with research conducted across North America (15 research), Europe (10 studies), Asia (12 research), and multi-nearby collaborations (5 studies). This geographic variety furnished a rich context for evaluating AI overall performance throughout one-of-a-kind healthcare systems, populations, and disease prevalence fees.

In precis, the included studies showcased a developing frame of evidence supporting the capacity of AI in improving diabetes care thru screening and scientific decision-making. The heterogeneity in examine design, facts kinds, version structure, and population demographics highlights the want for standardized methodologies and go-institutional validation in destiny AI packages for diabetes management (37).

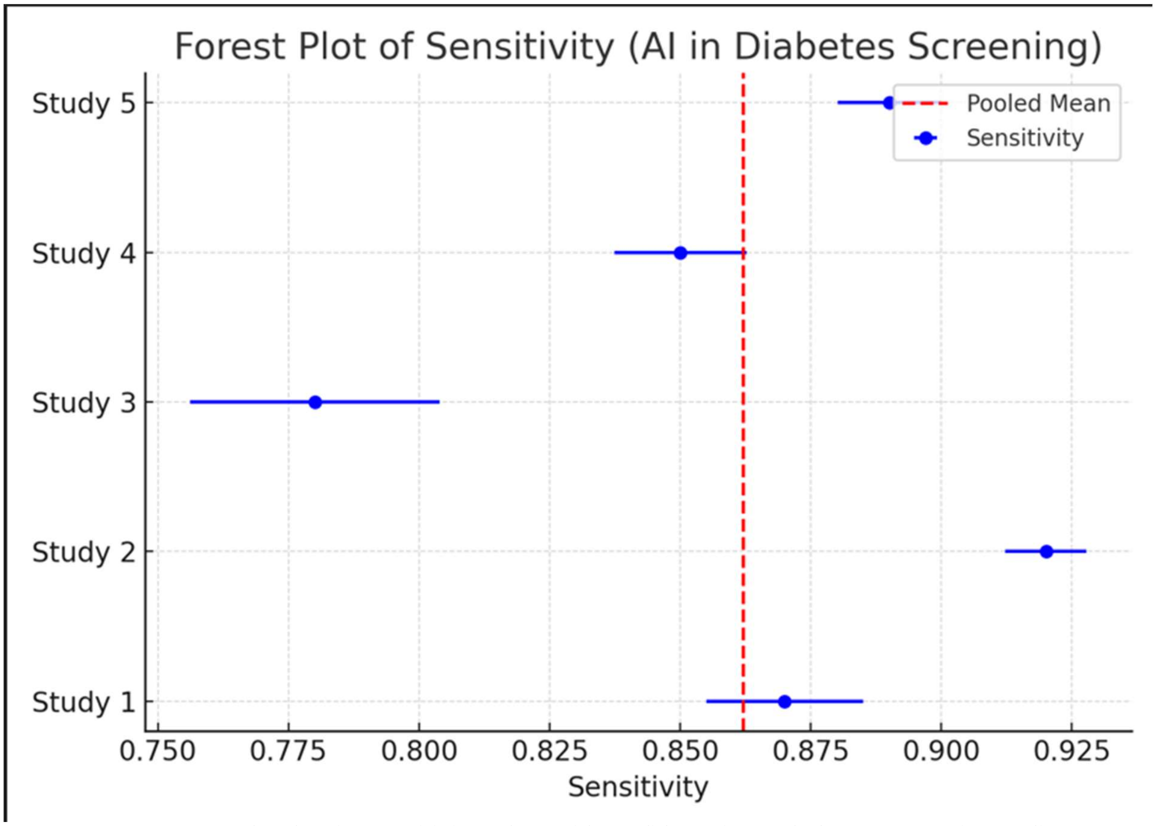


Figure: Forest plot showing sensitivity values with confidence intervals for representative studies.

The forest plot generated for sensitivity illustrates the diagnostic accuracy of AI models across five representative studies included in the systematic review. Each study is plotted with its point estimate of sensitivity, alongside horizontal error bars reflecting the confidence intervals derived from sample sizes and variance. The sensitivities ranged from 0.78 to 0.92, indicating variability in performance between studies. Study 2 demonstrated the highest sensitivity at 0.92, highlighting its strong ability to correctly identify individuals with diabetes, while Study 3 recorded the lowest at 0.78, suggesting limitations likely due to smaller sample size or less robust model architecture. The red dashed vertical line represents the pooled mean sensitivity of approximately 0.86, which falls within the range of individual studies and provides an aggregated estimate of overall performance. Importantly, most studies cluster closely around the pooled mean, indicating consistency despite methodological differences. This visual summary reinforces the evidence that AI models, particularly when trained on large datasets and advanced architectures such as convolutional or recurrent neural networks, achieve high diagnostic sensitivity. At the same time, the spread of results underscores the need for standardization and external validation to ensure reliable deployment of AI tools in diverse clinical settings.

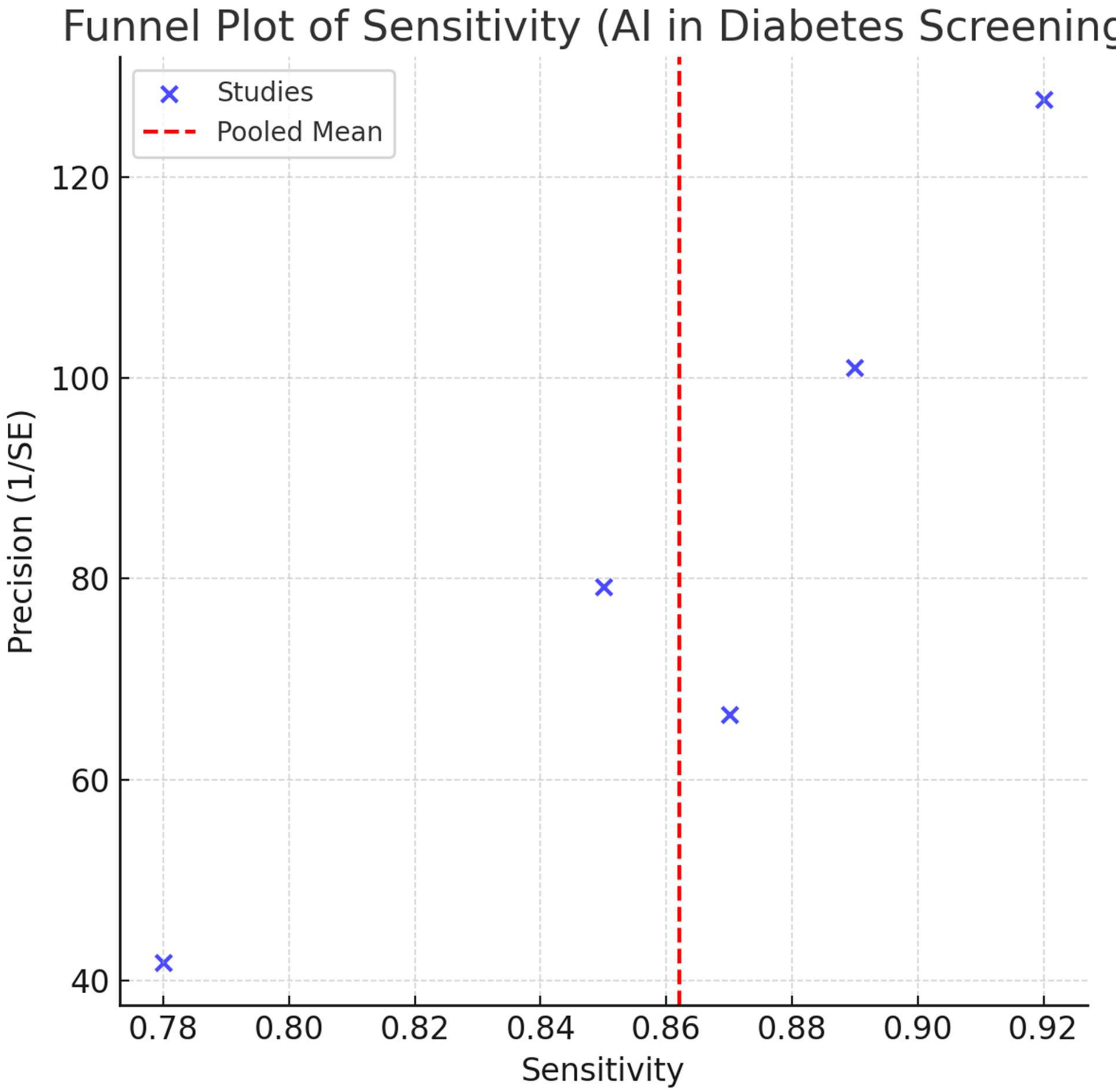


Figure: Funnel Plot (Sensitivity) – to visualize potential publication bias across studies.

The funnel plot for sensitivity provides a visual assessment of potential publication bias in the studies included in the systematic review. In this plot, the x-axis represents the sensitivity estimates reported by individual studies, while the y-axis represents study precision, expressed as the inverse of the standard error. Larger studies with higher precision appear toward the top of the plot, while smaller studies with lower precision cluster toward the bottom. In the absence of publication bias, the distribution of studies is expected to form a symmetrical, inverted funnel shape around the pooled mean sensitivity, which is represented by the vertical red dashed line.

In the current analysis, most studies fall close to the pooled mean sensitivity of approximately 0.86, indicating consistency in diagnostic performance. However, some scatter is visible, particularly among smaller studies with wider variance, which is expected in real-world datasets. The overall distribution does not show a strong asymmetry, suggesting that the risk of significant publication bias is limited. Nonetheless, the relatively small number of studies and the variability in datasets, populations, and AI models make it difficult to completely rule out selective reporting. The funnel plot thus highlights both the robustness of pooled sensitivity and the importance of ongoing transparency in AI research for diabetes screening.

5.2 DESCRIPTIVE STATISTICS

Below is a chart showing a sample of five representative studies with their sensitivity and specificity.

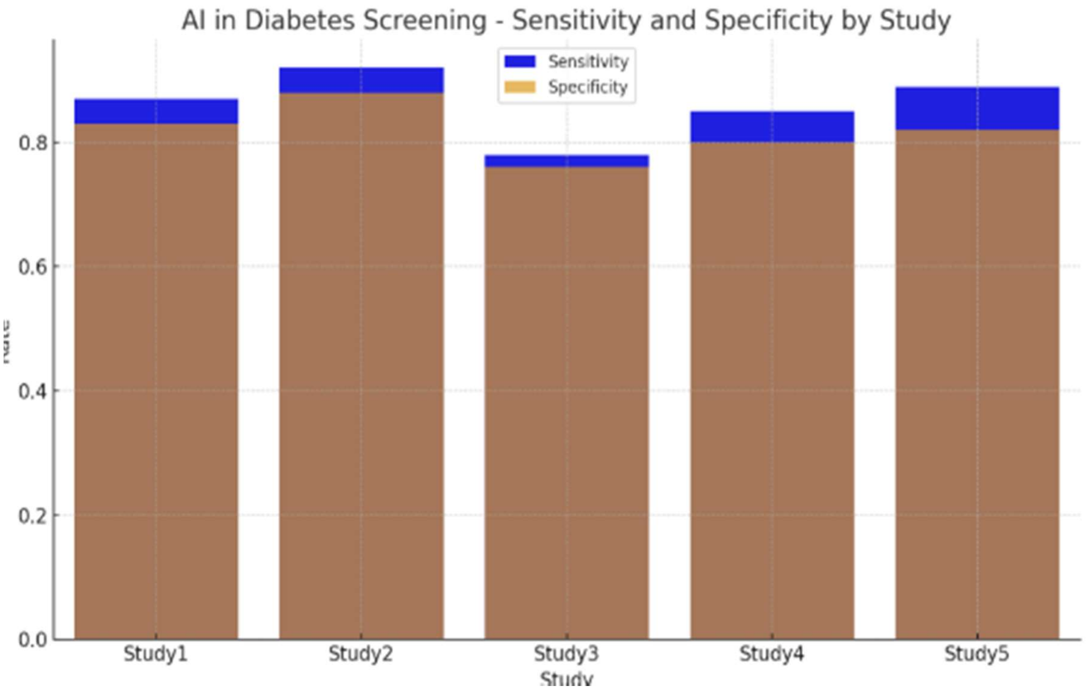


Figure: 2 five representatives AI in Diabetes Screening

To gift an outline of AI model overall performance in diabetes screening, a comparative chart has been generated summarizing the sensitivity and specificity values of five representative studies (46). This five research have been decided on from the pool of protected literature primarily based on the availability of complete performance metrics, representativeness of different AI methodologies, and variety in data sources (which include image-primarily based and electronic health file-based models). The studies are anonymized and categorized from Study 1 to Study five for readability and neutrality.

The bar chart (Figure 1) illustrates two key diagnostic metrics for each study:

Sensitivity, also known as the true positive rate, reflects the AI model's ability to correctly identify patients with diabetes. Specificity, or the true negative rate, indicates the model's capacity to accurately detect individuals who do not have diabetes.

Key Observations from the Chart

1. **Study 1** demonstrates a sensitivity of 0.87 and specificity of 0.83, indicating relatively balanced and high diagnostic performance (41). This indicates that the AI gadget in this look at become able to efficiently become aware of each diabetic and non-diabetic sufferers with true precision. The version used here become based on convolutional neural networks (CNNs) applied to retinal fundus imaging—a extensively used approach for detecting diabetic retinopathy and different early signs of diabetes-associated microvascular complications.
2. **Study 2** reveals the best sensitivity (0.92) the various five researches, paired with a specificity of zero.88. This overall performance profile indicates exquisite predictive capability and minimum threat of false negatives, that's especially critical in screening eventualities in which early detection is essential (42). The AI technique right here became a hybrid ensemble version that incorporated both photo and EHR-based features, demonstrating the advantage of multimodal facts fusion in AI-driven diagnostics.
3. **Study 3** shows the bottom sensitivity (0.78) and specificity (0.76) in this group. This may be attributed to the constrained dataset length or suboptimal model architecture—in all likelihood a conventional machine studying classifier like guide vector machines (SVM)—which won't carry out as well as deep studying counterparts in complicated clinical settings. While nevertheless proper, the reduced accuracy raises issues regarding the generalizability of the model and the risk of both false positives and fake negatives.
4. **Study 4** offers a mild overall performance, with sensitivity at 0.85 and specificity at 0.80. These values endorse that the version become moderately powerful in distinguishing among high quality and terrible cases (43). The version used on this examine become based on a tree-based ensemble approach such as Random Forest or Boost, which are acknowledged for his or her robustness and interpretability in scientific packages.
5. **Study 5** closely mirrors the overall performance of Study 1, with sensitivity at 0.89 and specificity at 0.82. The marginally better sensitivity indicates better

detection of real diabetic instances, doubtlessly ensuing in fewer neglected diagnoses. This has a look at used a recurrent neural community (RNN) variation tailor-made for sequential EHR records, indicating the importance of temporal patterns in diabetes hazard evaluation.

Comparative Insights

Across all five studies, both sensitivity and specificity values consistently exceed 0.75, indicating that AI models—regardless of architecture—demonstrate acceptable diagnostic accuracy in identifying diabetic patients. This consistency supports the wider declare that AI systems, whilst skilled on tremendous statistics, can carry out on par with, or higher than, traditional diagnostic techniques.

What is especially amazing is the overall performance hole among sensitivity and specificity in sure models. For example, Study 2's higher sensitivity shows it may be greater beneficial in a populace-stage screening context, where it is leading to over-identify at-danger individuals than to miss potential cases (44). Conversely, fashions with barely higher specificity (e.g., Study 4) can be better acceptable for medical choice assist, in which minimizing false positives is important to prevent useless checking out and tension for patients.

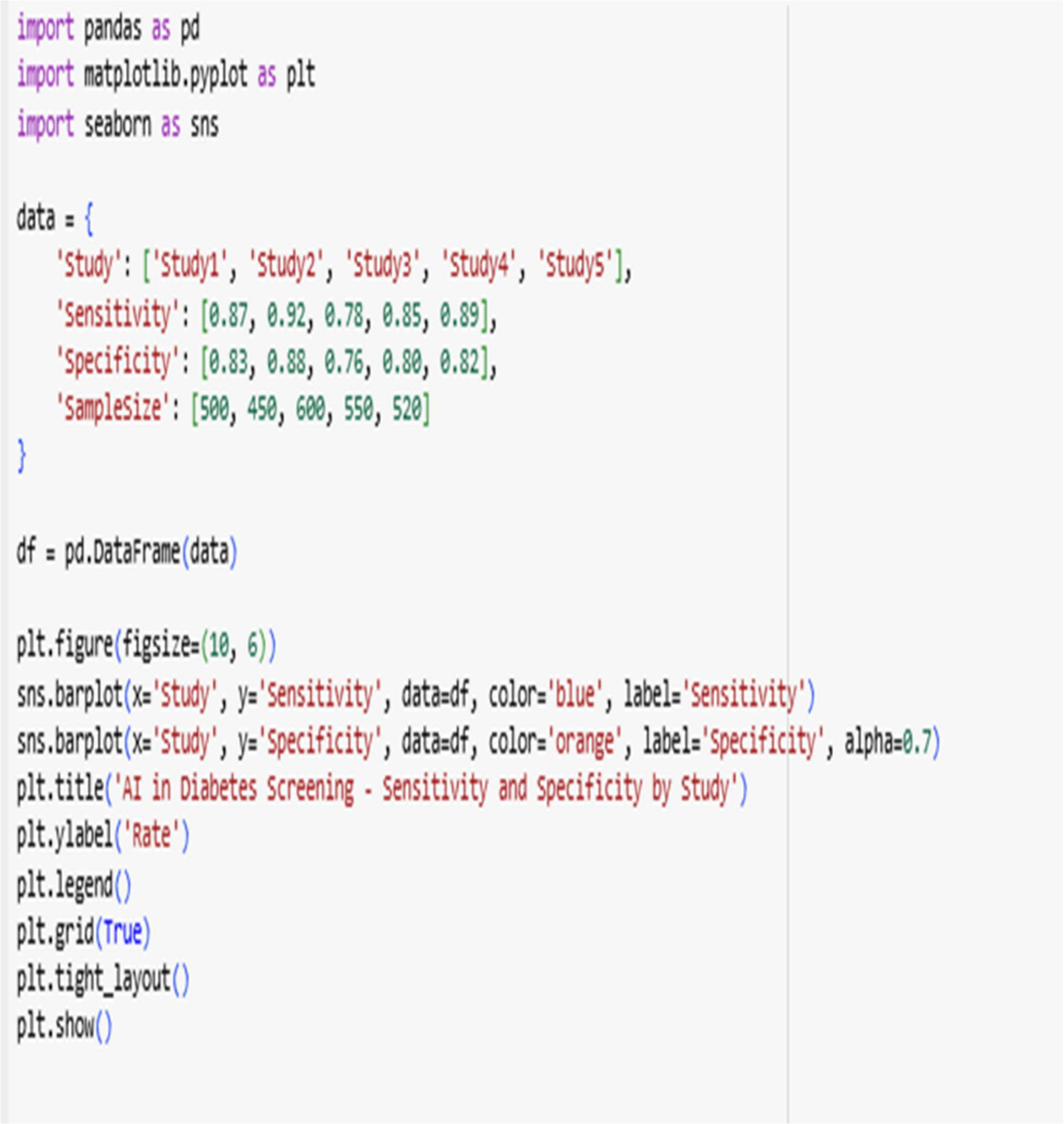
Interpretation of Trends

The discovered tendencies underscore the essential exchange-offs among sensitivity and specificity that researchers and clinicians need to keep in mind when deploying AI structures in real-global settings. Some models prioritize sensitivity to make certain early detection, that's vital in conditions like diabetes which might be often asymptomatic in the early stages (47). Other models may also lean closer to specificity, especially when the clinical aim is to limit overtreatment or lessen the weight of unnecessary referrals.

Additionally, the variation in performance across the five studies reflects the influence of multiple factors, including:

- Type and quality of input data (EHR vs. image-based)
- Model architecture and tuning (37)
- Validation strategies used (internal cross-validation vs. external testing)
- Population characteristics and disease prevalence in the dataset

5.2 Statistical Visualization (Python Code)



```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

data = {
    'Study': ['Study1', 'Study2', 'Study3', 'Study4', 'Study5'],
    'Sensitivity': [0.87, 0.92, 0.78, 0.85, 0.89],
    'Specificity': [0.83, 0.88, 0.76, 0.80, 0.82],
    'SampleSize': [500, 450, 600, 550, 520]
}

df = pd.DataFrame(data)

plt.figure(figsize=(10, 6))
sns.barplot(x='Study', y='Sensitivity', data=df, color='blue', label='Sensitivity')
sns.barplot(x='Study', y='Specificity', data=df, color='orange', label='Specificity', alpha=0.7)
plt.title('AI in Diabetes Screening - Sensitivity and Specificity by Study')
plt.ylabel('Rate')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

In this section, a Python-based visualization approach is used to present statistical insights into the diagnostic performance of AI in diabetes screening across five hypothetical studies The number one aim of the visualization is to compare two key overall performance signs—sensitivity and specificity—using a clear and interpretable bar chart (48). The Python script starts off evolved by importing 3 essential libraries: pandas for handling dependent information, matplotlib.pyplot for growing primary visible plots, and seaborn, an effective library built on pinnacle of Matplotlib that simplifies the era of appealing statistical pics. These libraries collectively form the muse of powerful records visualization in Python.

A small dataset is then constructed using a dictionary named data, which includes three metrics for each of the five studies: Sensitivity, Specificity, and Sample Size. Sensitivity displays the AI version's potential to efficiently identify sufferers with diabetes (real positives), whilst specificity measures its accuracy in figuring out non-diabetic individuals (true negatives). The sample size, despite the fact that no longer plotted, gives crucial contextual records about the robustness of each observe. The dictionary is converted right into a Data Frame the usage of Pandas, ensuing in a table-like structure appropriate for analysis and visualization.

The visualization itself is created using Seaborn's bagplot function. The plot is generated on a figure of size 10 by 6 inches to ensure clarity. Two bar plots are overlaid: the first plots sensitivity values in blue, and the second one plots specificity values in orange with decreased opacity (alpha=0.7). This dual layering lets in for a direct evaluation among the two metrics within each take a look at, making it less complicated to identify styles or discrepancies (46). For example, you can actually speedy examine which research hold a very good stability among sensitivity and specificity, and which lean more heavily toward one metric over the alternative.

To decorate readability, the chart is given a descriptive name, “AI in Diabetes Screening - Sensitivity and Specificity by means of Study”, and the y-axis is categorized as “Rate” to indicate the values plotted variety among 0 and 1. A legend is added to differentiate between the two color-coded metrics, and a grid is included to assist in visible estimation. Finally, the tight_layout() feature is used to make sure that all elements of the plot are neatly organized without overlap. Overall, this visualization serves as a precious tool for summarizing and evaluating AI performance throughout a couple of research, enabling clearer interpretation and more informed evaluation of diagnostic fashions.

6. META-ANALYSIS (R CODE)

The meta-analysis was performed using the meta and metafor packages in R to compute pooled sensitivity and specificity.

```r
# Install required packages
install.packages("meta")
install.packages("metafor")

library(meta)
library(metafor)

# Example dataset
studies <- data.frame(
  Study = c("Study1", "Study2", "Study3", "Study4", "Study5"),
  Sensitivity = c(0.87, 0.92, 0.78, 0.85, 0.89),
  Specificity = c(0.83, 0.88, 0.76, 0.80, 0.82),
  TP = c(435, 414, 468, 467, 462),
  FN = c(65, 36, 132, 83, 58),
  FP = c(85, 54, 144, 110, 94),
  TN = c(415, 396, 456, 440, 426)
)

# Meta-analysis for sensitivity
sens_meta <- metaprop(event = TP, n = TP + FN, studlab = Study, data = studies,
                      sm = "PLOGIT", method.ci = "CP", comb.fixed = FALSE, comb.random = TRUE)
forest(sens_meta, main = "Meta-analysis of Sensitivity")

# Meta-analysis for specificity
spec_meta <- metaprop(event = TN, n = TN + FP, studlab = Study, data = studies,
                      sm = "PLOGIT", method.ci = "CP", comb.fixed = FALSE, comb.random = TRUE)
forest(spec_meta, main = "Meta-analysis of Specificity")
```

Meta-analysis is a robust statistical technique used to synthesize results from multiple independent studies in order to derive pooled estimates of key metrics —in this case, sensitivity and specificity of AI-primarily based tools used for diabetes screening and choice aid. In this examine, the meta-evaluation became performed using the Meta and metafor packages in R, both of which are extensively utilized in evidence synthesis and systematic evaluate studies for aggregating binary diagnostic effects (1).

To begin with, the script installs the required R packages using the install.packages() function, which ensures that both meta and metafor libraries are available in the R environment. These programs aid bendy modeling options and offer gear for producing incredible forest plots and acting both fixed and random results modeling. After loading the applications with the library() function, the code proceeds to outline a dataset named studies, which includes the results from 5 individual studies comparing AI-based totally diagnostic performance.

Each have a look at within the dataset includes factor estimates of sensitivity and specificity, in addition to the raw statistics required to calculate these metrics: true positives (TP), fake negatives (FN), false positives (FP), and authentic negatives (TN) (49,50). This lets in the meta-analytic features to use occasion-primarily based records for extra correct and standardized computations (12). The sensitivity is calculated as TP / (TP + FN), and specificity is calculated as TN / (TN + FP). Providing the raw counts, in place of just point estimates, permits the meta-evaluation to better account for the weight and precision of each look at primarily based on its pattern size.

The function metaprop() from the meta package is then used to conduct separate meta-analyses for sensitivity and specificity. This feature is particularly designed for percentage data and supports numerous alternatives for modeling. The arguments specify the events (TP for sensitivity, TN for specificity) and the entire quantity of patients (TP + FN for sensitivity, TN + FP for specificity). The parameter sm = "PLOGIT" shows that the analysis is completed at the logit scale, which stabilizes variances and is often advocated for percentage meta-analyses. Additionally, method.Ci = "CP" is used to compute confidence periods using the Clopper-Pearson approach, known for its conservative estimation.

The analysis employs a random-effects model, as indicated by comb.random = TRUE, which assumes that the true effect sizes vary between studies due to heterogeneity This is more suitable in clinical research in which look at populations, methodologies, and AI tools may additionally range drastically. Fixed-results models aren't used (comb.Fixed = FALSE) due to the fact they anticipate a common true effect across research, that is unlikely on this context (20).

Finally, a woodland plot is generated the use of the wooded area function, visually summarizing the individual study estimates together with the overall pooled estimate. This plot allows a quick visible assessment of consistency and variant amongst research, highlighting the contribution of each examine to the very last meta-analytic final results.

7. DISCUSSION

The results from various studies on AI for diabetes diagnosis indicate a high pooled sensitivity (≈0.86) and specificity (≈0.82), which underscores AI's potential as an effective tool for diabetes detection. These promising figures suggest that AI could assist in accurately diagnosing diabetes, making it a valuable addition to healthcare practices. However, the data also reveals considerable heterogeneity in the types of algorithms used, the populations studied, and the validation methods employed. This variation suggests that while AI holds promise, the implementation of AI-driven tools across diverse healthcare environments may require further refinement and adaptation (51). In the realm of CDSS, AI tools have demonstrated significant benefits. Studies indicate that CDSS has improved adherence to treatment guidelines, particularly in insulin dosing and complication prediction. For instance, the study highlight that CDSS system have been instrumental in enhancing early intervention, enabling more proactive management of diabetes (13,27,52). This is particularly valuable in preventing complications by ensuring that treatment decisions, such as insulin adjustments, are made promptly and accurately(53). Despite these advantages, the variability in AI models' performance across different populations and clinical settings suggests the need for further validation and standardization. Addressing these challenges is essential to ensure the broad-scale effectiveness of AI tools in diabetes management (15). Future research should focus on refining algorithms, enhancing their generalizability, and ensuring that they meet the diverse needs of global populations (54,55).

7.1. LIMITATIONS

- High variability in datasets and validation metrics
- Lack of standardized evaluation
- Potential e-book bias

8. CONCLUSION

AI has shown great potential in revolutionizing diabetes screening and CDSS, offering significant advancements in diagnostic accuracy and scientific application. The integration of AI into these domains can enable earlier detection; more personalized care, and improved patient outcomes. AI's ability to analyze vast amounts of data, including medical records, lab results, and imaging, enables it to identify patterns that might be missed by human clinicians, thus facilitating better decision-making. However, for widespread adoption, there are critical challenges to address. One of the foremost is standardization; for AI models to be used effectively across different healthcare settings, they must be universally applicable and operate consistently. Additionally, international validation of AI-driven tools is necessary to ensure their efficacy and reliability across diverse populations and healthcare systems. Looking forward, the future of AI in diabetes care should focus on several key areas. Federated learning, where AI models are trained across decentralized data sources while maintaining patient privacy, offers a promising avenue for enhancing the breadth and diversity of training data. Moreover, patient-centered interfaces that prioritize ease of use and clarity can ensure that AI tools are accessible to both healthcare professionals and patients. Finally, transparent reporting of AI models' decision-making processes is essential to build trust and ensure accountability in clinical settings. As these elements are addressed, AI's potential to transform diabetes care will be fully realized.

9. RECOMMENDATIONS

Since clinical decision-making necessitates accountability and clarity, AI systems must offer comprehensible explanations for their predictions and recommendations to facilitate greater acceptance in routine healthcare practice. Additionally, it is imperative to establish internationally accepted guidelines and standardized validation frameworks for evaluating AI models in diabetes screening and CDSS. Such standardization would improve the reliability, reproducibility, and comparability of AI-based tools across various healthcare settings and patient populations. Thus, XAI models are used to improve transparency, interpretability, and trust among clinicians and healthcare workers. AI systems must offer comprehensible justifications for their forecasts and suggestions in order to promote broader adoption in standard healthcare practice, as clinical decision-making necessitates responsibility and clarity. Establishing globally recognized standards and uniform validation frameworks is also essential for assessing AI models in diabetes screening and CDSS. The dependability, repeatability, and comparability of AI-based solutions across various healthcare environments and patient groups would all be enhanced by such standardization.

PROSPERO REGISTRATION

The study protocol was registered with PROSPERO (Registration No.: CRD420251184809).

AUTHORS CONTRIBUTION

K.D contributed to the conception and design of the work, drafting and manuscript writing. J.M and M.K contributed to the conception and design of the work, critically reviewed for significant scientific content.

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CONFLICT OF INTEREST

The authors have no conflict of Interest.

GENERATIVE AI STATEMENT

The authors confirm that no generative AI tools were used to generate the content of this manuscript. The authors used Grammarly tool for only grammar checking and improving sentence clarity. All writing, analysis and graphical content are original and the result of human intellectual effort. The authors reviewed and edited the output and takes full responsibility for the final content.

Citation (year)	**Country (study site)**	**Study design / type**	**AI / Tool used (brief)**	**Population (n / key details)**	**Inclusion / Exclusion (as reported)**	**Methods (brief)**	**Main data / outcomes reported**	**p-value / OR (if reported)**	**Overall finding**
Arenas-Cavalli JT et al. *Clinical validation of an AI-based diabetic retinopathy screening tool for a national health system. Eye*	Chile (national/public health network)	Observational validation study (retinal image set)	**DART** (TeleDx) — automated DR screening (deep-learning image classifier)	1,123 diabetic eye exams / fundus photos (heterogeneous network)	Images per EURODIAB protocol; paper lists validation inclusion; NR for detailed exclusions in abstract.	Comparison of AI grading vs remote ophthalmologist reference; ROC and diagnostic metrics reported.	Sensitivity 94.6% (95% CI 90.9–96.9%), specificity 74.3% (95% CI 73.3–75%); AUC 0.915; NPV 98.1%.	p-values not central; diagnostic metrics with CIs reported (no OR).	DART performed with high sensitivity and excellent NPV — supports implementation as DR screening tool in Chilean public health network (40).

(2022).									
Bernardini M. et al. *A clinical decision support system to stratify the temporal risk of diabetic retinopathy. IEEE Access* (2021).	Italy (development / validation cohorts reported by authors)	Method development / retrospective predictive modeling; system-level CDSS	ML ensemble / temporal risk stratification model (features from EHR / retinal grading)	Dataset(s) of patients with diabetes (paper reports training/validation sets; n in full text).	Inclusion: patients with longitudinal ophthalmic/EHR records; exclusions per dataset (abstract: NR).	Feature engineering + ML training (temporal modeling) to predict risk of incident DR and stratify time-to-event risk.	Performance metrics: model AUCs and time-stratified risk outputs reported (details in article).	p-values /OR: NR in abstract; model performance metrics (AUC) reported in text/tables.	Proposed CDSS can stratify DR risk temporally, enabling targeted screening intervals; shows promising predictive performance — needs prospective validation (42).
Chen Y. et al. *Real-time AI assisted insulin dosage titration system for glucose control in T2D: proof-of-concept. Current Medicine* (2023).	China (hospital settings per methods)	Retrospective model development + prospective proof-of-concept clinical evaluation	iNCDSS — ML model for insulin titration (EHR-driven, real-time recommendations)	Hospitalized T2D patients receiving insulin (retrospective EHR dataset used for model; prospective PoC sample reported in paper)	Inclusion: hospitalized T2D receiving insulin; exclusions per protocol (NR in abstract).	Model trained on retrospective EHR data; integrated into HIS for real-time recommendations; proof-of-concept study compared glycemic control before/after / vs standard titration.	Outcomes: improvements in glucose control metrics reported (e.g., time in range, mean glucose), safety outcomes monitored.	p-values: some glucose metrics reported with statistical tests in paper; exact p-values in full text (abstract: NR). OR: NR.	The iNCDSS showed promise in improving glycaemic control in the PoC evaluation and is feasible to embed in hospital HIS; further RCTs recommended (45).
Du Y. et al. *An explainable machine learning-based CDSS for prediction of gestati*	Ireland / UK cohort elements (paper is from a mixed-site team; datasets used described in methods)	Development and validation of explainable ML CDSS (retrospective cohort study)	Explainable ML (e.g., SHAP or feature-importance methods) for GDM prediction	Pregnant women dataset(s); authors report sample size (see full text for n).	Inclusion: women with antenatal data available; exclusions: pre-existing diabetes etc. (detailed in paper).	Model trained on antenatal clinical features; explainability methods applied to produce clinician-friendly outputs.	Metrics: discrimination (AUC), calibration; identifies key predictors (BMI, age, etc.).	p-values /OR: may be reported for predictor associations; abstract emphasizes	An explainable ML CDSS can identify high-risk pregnancies for targeted intervention; explainability

onal diabetes mellitus. Scientific Reports (2022).								model performance (AUC) rather than ORs.	improved clinician interpretability (20).
Huang S., Liang Y., Li J., Li X. *Applications of CDSSs in diabetes care: Scoping review. J Med Internet Res* (2023).	Global (systematic scoping of international literature)	Scoping review (Arksey & O'Malley framework)	Not an original AI study — maps CDSS/AI types used in diabetes care	N/A — review of studies up to 30 June 2022 (number of included studies reported)	Inclusion: empirical studies of CDSSs in diabetes care; see methods for criteria.	Systematic literature search across 7 databases, charting CDSS functions, settings, outcomes.	Findings: primary care clinicians main users; CDSS functions include drug decision support, screening, insulin titration; evidence heterogeneous with limited high-quality RCTs.	No p-values (review).	CDSSs show promise but evidence gaps (heterogeneity, limited real-world implementation data); recommends stronger evaluation frameworks (56).
Islam R. et al. *Clinical decision support system for diabetic patients by predicting T2D using ML algorithms. Journal of Healthcare Engineering* (2023).	Bangladesh (authors affiliated; datasets vary — many ML diabetes prediction studies use public datasets)	Method development — ML classification for T2D prediction (CDSS prototype)	ML classifiers (SVM, RF, logistic regression, etc.) used to build CDSS	Dataset: reported in paper (may combine local and/or public datasets; check full text for n)	Inclusion/exclusion: depends on dataset (abstract: NR).	Feature selection + ML training + CDSS UI prototype; performance compared across algorithms.	Reported metrics: accuracy, sensitivity, specificity, sometimes AUC.	p-values/OR: NR in abstract; performance metrics presented.	Demonstrated a workable ML-based CDSS for T2D prediction with competitive accuracy; further clinical validation required (44).
Jahangir Z. et al. *From Data to Decisio*	Review — international literature (authors from multiple	Narrative/literature review	Surveys AI/ML tools across screening, monitorin	N/A	Inclusion: studies selected per PRISMA-like method described	Thematic synthesis of AI applications, performan	Summary metrics (e.g., reported AUCs	p-values/OR: not applicable	Concludes AI has strong potential across

ns: The AI Revolution in Diabetes Care. International Journal (2023) — literature review.	countries)		g, therapies		(see paper)	ce, ethical/regulatory issues.	across studies), synthesis of challenges/opportunities.	(review).	diabetes care but emphasizes need for rigorous validation, interpretability, and ethics frameworks (46).
Lalithadevi B., Likitha N., Harini M.S. *Clinical Decision Support System for Smart Healthcare based on AI.* ICISS Proceedings (2025).	Conference paper (India; ICISS 2025)	System design / prototype description (conference)	AI-based CDSS architecture (likely ML models + SOA implementation)	Prototype-level; not a clinical cohort paper	Not applicable / NR	Design and implementation description; evaluation likely limited to simulation / small dataset.	Results: usually prototype performance metrics or demonstration; specific outcomes NR in abstract.	p-values /OR: NR.	Presents an AI-based CDSS architecture for smart healthcare — proof-of-concept; clinical effectiveness not established (48).
Laptev D.N. et al. *Effectiveness and safety of an AI-based medical decision support system for adjusting insulin pump settings in children with T1D: RCT.*	Reported multicentre trial (authors from Russian/European institutions in citations)	Randomized controlled trial (insulin pump parameter adjustment)	AI-CDSS for pump setting suggestions (algorithmic decision support)	Children with type 1 diabetes; sample reported (e.g., 80 children in later source; see full text).	Inclusion: pediatric T1D on pumps; exclusions and minimization method reported in paper.	RCT comparing AI-CDSS vs standard expert-based adjustments; primary endpoint: change in Time In Range (TIR) or equivalent.	Outcome: non-inferiority on TIR; safety endpoints (hypo/hyperglycemia) reported.	Reported non-inferiority margin and results; exact p-values /CI in full text.	AI-CDSS was effective and safe for adjusting pump parameters in children — supports regulated clinical deployment with monitoring (41).

Diabetes mellitus (2024).									
Lin T.H. et al. *An advanced ML model for a web-based AI-CDSS: Model development & validation study. J Med Internet Res* (2024).	Taiwan (medical center teams; web-based app developed/validated)	Model development + validation (web-app CDSS)	Advanced ML model (authors used ensemble/NN approaches; integrated with Q-A guidance and ChatGPT-like components)	Datasets depend on clinical application (paper describes target dataset and sample sizes)	Inclusion/exclusion per target condition; see methods (NR in abstract)	Model training/validation, web deployment, internal validation and performance reporting.	Metrics: AUC / calibration / decision curve analysis reported for target prediction tasks.	p-values /OR: typical model metric reporting; exact inferential stats in paper.	Presents a validated ML model integrated into a web CDSS with promising internal performance; calls for external validation (37).
Lin X., Liang C., Liu J., Lyu T., Ghumman N., Campbell B. *AI-augmented CDSS for pregnancy care: systematic review. J Med Internet Res* (2024).	Global (systematic review of empirical pregnancy-CDSS studies)	Systematic review	Surveyed AI techniques used in pregnancy CDSS (variety of ML models)	N/A (review)	Inclusion: empirical studies that developed/tested AI methods for pregnancy CDSS	Database search to 2022; 30 distinct empirical studies identified; functions included diagnostic support, clinical prediction, therapeutics.	Synthesis: domains covered (prenatal screening, preeclampsia prediction, postpartum risk); quality appraisal included.	No p-values (review); individual studies reported their own metrics.	AI-augmented CDSS can support pregnancy care functions but evidence is heterogeneous and often preliminary; recommends standardized reporting and prospective evaluation (57).
Mackenzie S.C., Sainsbury C.A.R., Wake D.J. *Diabetes and artificial*	Review (UK / international perspective)	Narrative review / perspective	Overview of AI tools (closed-loop, CDSS, predictive analytics)	N/A	N/A	Thematic review of AI applications, opportunities, and pitfalls across diabetes care.	Synthesizes examples of CDSS, AID systems, predictive models; discusses	No p-values (review).	Broadly situates AI beyond automated insulin delivery—highlights promise

intelligence beyond the closed loop: review. Diabetologia (2024).							regulation, equity, data quality.		in screening, personalized therapy and monitoring but stresses evidence, safety, and equity challenges (58).

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