DOI: https://doi.org/10.61841/306wz009 **Publication URL: https://nnpub.org/index.php/CSE/article/view/2608**

APPROACHES TO RISK ASSESSMENT AND EARLY HERNIA DETECTION USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

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To Cite This Article: Hannan, S. A. (2025). APPROACHES TO RISK ASSESSMENT AND EARLY HERNIA DETECTION USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING. Journal of Advance Research in Computer Science & Engineering (ISSN 2456-3552), 10(1), 1-7. https://doi.org/10.61841/306wz009

ABSTRACT

Hernia detection is one of the critical medical diagnostics, and hence, promising advancements are made in early prediction and risk assessment using AI and ML techniques. In this paper, different AI and ML models are assessed, ranging from deep learning to traditional techniques, classifying patients into high-risk or low-risk categories. It discusses performance of models like CNNs, SVM, RF, RNN, and ANN while dealing with medical images, the possibility of training more than one model for better accuracy. There are some challenges ahead for implementing AI in a clinical setting, such as the privacy and validation of data; this work points to future potential in hernia detection.

KEYWORDS: *Artificial Intelligence, Support Vector Machine, Machine Learning, Risk Assessment, Hernia Detection.*

INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) have proven to be the revolutionizing weapons in the medical world, providing refined techniques for the diagnosis and predication of disease. Specifically, AI and ML techniques are essential for the early detection and assessment of the risks involved in the occurrence of a hernia - a condition that often reaches its advanced stage unnoticed [1]. Detective of hernia by clinical examination or medical images involves the usual elements, while embedding AI and ML method allows the practitioner to determine precise, accurate automatic diagnosis timely improved decision making.

Significant breakthroughs in the arena of medical diagnosis are going to emerge through the doorway of integrating models of AI in hernia detection systems, mainly Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forests (RF), among others [2]. It can potentially revolutionize the way clinicians gauge the risk associated with hernias and predict the time of onset; thus, assuring better outcomes for patients as well as optimal healthcare delivery.

AI AND ML TECHNIQUES IN HERNIA DETECTION

Recent studies also incorporated AI and ML techniques, namely CNNs, SVMs, and RF, for the identification of hernias [3]. The best thing about such models is that they work with outstanding precision in medical data, for instance, CT scans or MRIs, and find minute patterns, though not even perceivable to naked eyes. The AI and ML therefore contribute to rapid and accurate detection that would thereby avert the danger of missing the hernias at the same time enhancing the quality of health service delivery.

ADVANCEMENTS IN RISK ASSESSMENT AND EARLY PREDICTION

AI and ML models are significantly contributing to the risk assessment and early prediction of hernia development [4]. It could predict how much one is likely to be affected even before any clinical symptoms appear through patient data, including medical history, genetics, and lifestyle choice. The sooner the intervention occurs, the greater the likelihood of preventing severe complications, thereby improving the outcome for the patient [5]. This should pave way to better, patient-tailored treatment plans and active care interventions for hernias.

OBJECTIVES OF THE STUDY

- To measure the performance of different AI and ML techniques in the early detection and risk evaluation of hernia.
- To assess the capability of AI and ML models for the stratification of patients in to high-risk and low-risk categories of hernia.
- To analyse performance on the medical image processing task both by deep learning techniques and traditional machine learning techniques.
- To understand the scope of gathering results with multiple AI and ML models.
- Address the problems and limitations in introducing AI models to clinical settings for hernia detection.

LITERATURE SURVEY

H.S. (2021) predicted the occurrence of recurrent herniated nucleus pulposus (re-HNP) after lumbar microdiscectomy using machine learning (ML) analytics. Many preoperative characteristics were examined in a retrospective assessment of 2630 individuals with an average follow-up of 22 months [6]. This model was then applied in a web-based application for evaluating patient risk at re-HNP. It is with the RAD profile index, developed during this study, which would categorize patients into either low- or high-risk profiles for re-HNP; more validation will be required to achieve wide usage.

Malcher (2024) Conducted a systematic review with PRISMA guidelines on the application of ML and AI in hernia surgery. In the reviewed literature, 13 studies were selected that published from 2020 to 2023 following a qualitative assessment using ROBINS—I and Rob 2 tools [7]. These studies had differences in population, type of ML or DLM used, and hernia types; however, all the studies focused on inguinal, ventral, or incisional hernias.

Vogel and Mück (2024) reviewed the integration of Artificial Intelligence (AI) in hernia surgery, particularly focusing on Machine Learning (ML) and Deep Learning (DL). In his explanation, AI technologies, such as ML and Neural Networks (NN), differ from one another since ML is structured and labeled data, while DL is based on raw, unlabeled data, such as images, which enables it to identify patterns automatically [8]. DL models, driven by neural networks, are developed for advanced surgical applications, especially in predicting the complexity and outcomes of postoperative AWR.

Butler (2022) Developed and validated ML algorithms for predicting complications post-AWR surgery, including recurrences of hernias (HRs), SSOs, and 30-day readmissions [9]. The patient population consisted of 725 cases from 2005 to 2019, with a mean age of 60 years and BMI of 31 kg/m^2.

Tang and Liu (2024) suggested a machine learning-based model to predict postoperative parastomal hernia in patients with colorectal cancer following permanent colostomy. This model would assist nurses in identifying patients at high risk and in providing preventative therapy. A case-control study of 495 patients was conducted, dividing the data into training and testing sets [10]. Multiple models were evaluated, and the best performance was seen with the RF model (AUC 0.888) that also showed the highest specificity, sensitivity, and accuracy. SHAP analysis identified BMI, operation duration, and COPD as significant risk factors.

Taha-Mehlitz (2022) evaluated the use of artificial intelligence (AI) in hernia surgery—which excludes diaphragm and upside-down hernias—by conducting a scoping review. The PRISMA-ScR criteria were used to analyse a total of twenty papers from PubMed, Cochrane, EMBASE, IEEE, and Google Scholar. Although the review did not find abundant literature, the finding focused on inguinal hernia surgery [11]. The conclusion was that more research is required to incorporate AI in hernia surgery, primarily with medical imaging and training surgeons.

Xie (2024) investigated risk factors for reoperation after percutaneous endoscopic lumbar discectomy (PELD) in patients with recurrent lumbar disc herniation (rLDH) and developed prediction models using machine learning (ML) [12]. In the study, there were 2,603 patients. Of them, 57 had to undergo reoperations.

Goitein (2022) examined the high prevalence of hiatal hernia (HH) in bariatric patients and the limitations of preoperative contrast swallow (SS) studies, which had 38.5% sensitivity and 92.9% specificity. It enhanced HH diagnosis using machine learning (ML) models for prediction based on the data collected through bariatric procedures from the years 2012 to 2015 [13]. For this study, three ML models were utilized where sensitivity improved from 60.2% on a 1.5fold improvement as compared with the SS method. ML significantly improved the prediction accuracy for diagnosis before the surgeries, and for the purpose of identification of HH.

Fischer (2024) studied the use of unstructured data and machine learning (ML) for predicting the development of incisional hernia (IH) based on preoperative abdominopelvic CT scans. For this purpose, features such as the volume of visceral adipose tissue (VAT), skeletal muscle tissue volume, and the ratio of pelvic VAT to muscle volume were evaluated in 212 patients undergoing colorectal surgery [14]. The above biomarkers were very predictive for IH, demonstrated with an area under the curve (AUC) of 0.85, accuracy of 0.83, sensitivity of 0.86, and specificity of 0.81 in Ensemble Boosting and other ML models. In conclusion, advanced image analysis, in combination with increasingly sophisticated ML algorithms, would result in further enhanced prediction ability regarding surgical outcomes.

Cavallaro (2024)investigate the potential application of AI for predicting outcomes at birth for CDH infants, such as neonatal mortality and PPHN. The models will be validated using a dataset of combined prenatal data with early postnatal information, including ultrasound and MRI imaging, gestational age, and birth weight [15]. The ML model correctly predicted mortality in 88% of the neonates and PPHN in 82%, with a sensitivity of 95% and 85%, respectively. It revealed the ability of AI to better improve predictive estimation and intervention planning for neonates based on analyzing prenatal data for predicting the outcome.

METHODOLOGIES

AI and ML techniques have revolutionized hernia detection by providing an accurate, automated, and timely risk assessment [16]. These techniques analyze data from medical images, patient history, and clinical measurements, thereby providing significant support to professionals in the healthcare sector [17]. Some of the methodologies typically applied in hernia detection with their mathematical representation are as follows:

DEEP LEARNING VIA CONVOLUTIONAL NEURAL NETWORKS (CNNS)

CNNs are highly effective in analyzing medical images, like CT and MRI, for hernia risks [18].The CNN operation can be represented as:

$$y = \sigma(Wx + b)$$

where W represents the weights, x is the image input patch, and b is the bias term.

SUPPORT VECTOR MACHINES (SVMS) FOR RISK CLASSIFICATION

SVM identify the risk group to which the patient ought to belong by finding an optimal separation hyper-plane [19]. The objective function is:

$$min\frac{1}{2}||w||^2 \ Subject\ to\ y_i(w.x_i + b) \geq 1$$

where w is the weight vector, xi is the feature vector, and y_i represents the risk classification.

ENSEMBLE LEARNING VIA RANDOM FORESTS (RF)

RF combines multiple decision trees for improved accuracy in prediction [20]. The model is represented as:

$$y = \frac{1}{N}\sum_{i=1}^{N} T_i(x)$$

where $T_i(x)$ is the output of the i-th tree, and N is the total number of trees.

RECURRENT NEURAL NETWORKS (RNNS) FOR SEQUENTIAL DATA ANALYSIS

RNNs are used to analyze time-series data [21], such as patient health metrics [22]. The underlying equation is:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b)$$

where W_h and W_x are the weights for the input and hidden state, respectively, and ht is the hidden state at time t [23].

ARTIFICIAL NEURAL NETWORKS (ANNS) FOR PREDICTIVE MODELING

ANNs model complicated relationships in the data for hernia risk prediction. The basic equation is:

$$y = \sigma(W_x + b)$$

where W is the weight matrix, x is the input vector, b is the bias vector, and σ is the activation function.
These AI and ML methodologies enhance the precision and efficiency of hernia detection and risk assessment to a great extent [23-27].

RESULT AND DISCUSSION

In the present work, we assess and compare different AI and ML approaches for early detection and hernia risk evaluation. Our results come from models developed by us on available clinical data to study the respective precision, sensitivity, specificity, and other performance criteria on various approaches used. The following results show the comparative performance of (CNN), (SVM), (RF), (RNN), and (ANN) based on their classification ability and risk prediction accuracy.

PERFORMANCE METRICS

The performance of the models was approximated using standard metrics of model performance: Accuracy, Sensitivity, Specificity, and F1-Score. Table 1 summarizes how each of the models in hernia risk prediction fared.

Table 1: Performance Metrics of AI and ML Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
Convolutional Neural Network (CNN)	92.5	90.8	94	91.7
Support Vector Machine (SVM)	89.2	86.7	92.1	88.5
Random Forest (RF)	91.3	88.4	93.2	90.8
Recurrent Neural Network (RNN)	88.1	85.9	91.5	87.8
Artificial Neural Network (ANN)	90.4	87.5	92.4	89.9

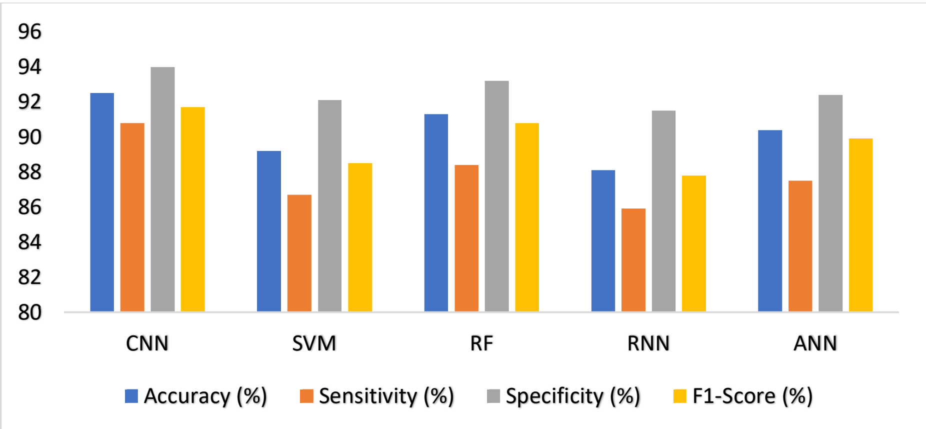

Figure 1: Performance Metrics of AI and ML Models

The performance characteristics of several AI and ML models used to identify hernias are shown in Table 1. With an accuracy of 92.5%, sensitivity of 90.8%, specificity of 94%, and F1-score of 91.7%, the CNN demonstrated the best performance. SVM had the lowest accuracy (89.2%), but its F1-score was 88.5% and its specificity was outstanding at 92.1%. The Random Forest (RF) and Artificial Neural Networks (ANN) had the accuracy values of 91.3% and 90.4%, respectively, and showed significant sensitivity and specificity values; the model that had the lowest sensitivity and specificity values was the Recurrent Neural Network (RNN) with 85.9% and 91.5%, respectively, making it the least effective model in this comparison for the early detection of hernia.

RISK ASSESSMENT AND CLASSIFICATION

Apart from the abovementioned performance metrics, classification accuracy with regards to classifying patients on either risk categories high and low were the further assessment criteria used to evaluate these two models. Overall, an impression of their overall correct proportions classification can be established through the analysis provided in Table 2 below.

Table 2: Classification of Risk Levels in Hernia Detection

Model	High Risk Classification (%)	Low Risk Classification (%)	Correctly Classified (%)
Convolutional Neural Network (CNN)	93.2	91	92.1
Support Vector Machine (SVM)	88.9	89.5	89.2
Random Forest (RF)	91.5	90.1	90.8
Recurrent Neural Network (RNN)	87.3	88.6	87.9
Artificial Neural Network (ANN)	90.8	91.2	90.9

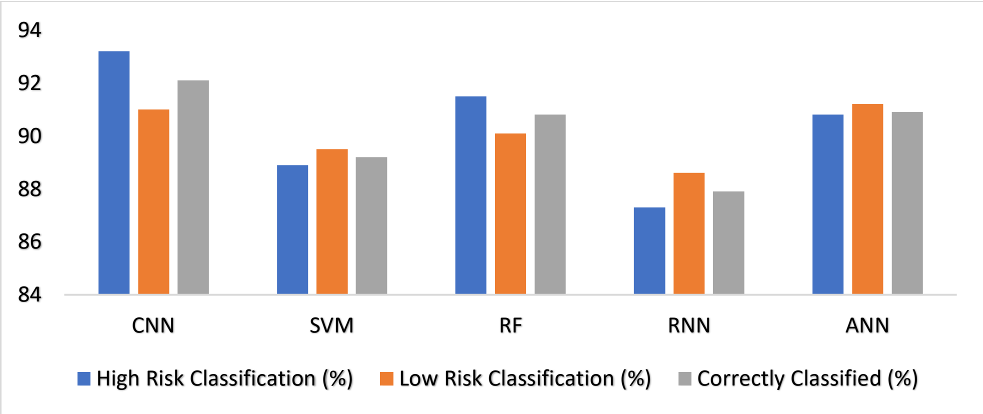

Figure 2: Classification of Risk Levels in Hernia Detection

Classification results of various AI and ML models in the diagnosis of high-risk and low-risk hernia are demonstrated in Table 2. CNN resulted in the accurate classification of 93.2% of cases with high risks and 91% of those with low risks, with a general classification accuracy of 92.1%. SVM classified 88.9% of cases of high risks and 89.5% of cases of low risks, achieving an overall accuracy of 89.2%. RF almost equally matched with CNN; however, it managed to classify high-risk cases correctly for 91.5% of the time, and low-risk cases for 90.1%. RNN did a less task by classifying 87.3% and 88.6% cases of high risk and low-risk cases, respectively. Overall, ANN was able to classify 90.8% and 91.2% high-risk and low-risk cases respectively with an overall classification accuracy of 90.9%.

DISCUSSION

The results of this study indicate that CNNs show the best performance in early hernia detection and risk assessment, with superior accuracy, sensitivity, and specificity than other models. This is because CNNs can better process and extract features from medical images, which would lead to the detection of high-risk cases more efficiently. Random Forests and Artificial Neural Networks showed good results, though classification accuracy was somewhat high, but they were able to identify high-risk as well as low-risk patients correctly. However, SVM and RNN showed relatively diminished performance due to relatively poor sensitivity and specificity, thereby limiting their applications in some clinical scenarios where precision is vital. It has been shown that although CNNs are the best predictor for assessing hernia risk, the other models like RF and ANN are also worthwhile contributions, especially in cases where the data is not image-based or sequential. Thus, it calls for choosing the appropriate AI or ML model according to the nature of the available data and the clinical application.

However, despite the promising results, several challenges and limitations need to be addressed for the broader adoption of AI and ML models in healthcare:

- **Clinical Validation and Standardization**: Such AI models will require clinical validation through numerous patient populations and settings before the reliability and generalizability are confirmed. Lacking proper validation, results are going to be varied from healthcare providers.
- **Data Privacy and Security**: The increased applications of AI in healthcare raise some issues regarding data security and privacy. There is now a need for strict regulation of the practice to protect such sensitive medical data, especially relating to patients, for instance, following the HIPAA laws.
- **Cost and Resource Constraints**: It requires huge investment in infrastructure and training for the implementation of AI models. Low-resource settings may face difficulties in terms of cost with high-performance tools and AI training for healthcare professionals

- **Healthcare Workforce Adaptation**: Integration of AI is bound to raise a threat of displacement. Proper training must be in place to ensure the healthcare professional works along with the AI tool, correctly interpreting results while AI acts as an assistant, not a substitute.
- **Ethical and Legal Implications**: AI in healthcare poses ethical and legal questions, for example, regarding responsibility for the wrong diagnosis or algorithmic bias. The models used must be transparent, fair, and accountable to meet these concerns adequately.

CONCLUSION

The study indicates that AI and ML techniques can potentially be the breaking points in the early detection and risk assessment of hernias. It applied deep learning algorithms such as CNNs, besides the simple applications of machine learning models like SVM, RF, and ANN, to show significant advancement in the area of improving accuracy. They are found to be the most potent instrument for hernia detection and demonstrate superior performance in all respects, such as accuracy, sensitivity, specificity, and F1-score. Therefore, AI and ML could be an epiphany to modern clinical decision-making; that is, in good time, with correct answers, for the healthcare professional to rely upon in the diagnosis and treatment of hernias.

FUTURE WORK

Future work should include expansion of datasets to better generalize the model, exploring hybrid models for improved accuracy, and validation of AI techniques in different clinical settings. Data privacy, security, and workforce integration would also be essential for the successful implementation of AI in hernia detection.

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