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REVIEW ARTICLE

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OPTIMIZATION OF SCREENING PROTOCOLS FOR CERVICAL CANCER USING MACHINE LEARNING ALGORITHMS: A SYSTEMATIC REVIEW AND META-ANALYSIS

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Abstract: Cervical cancer is a highly prevalent malignancy affecting women worldwide, ranking as the seventh most common cancer globally. This study aims to systematically review and analyze cervical cancer survival predictions using machine learning (ML) algorithms. A comprehensive search was conducted across Scopus and PubMed databases in February 2024. Extracted articles were screened using Hubmeta software, with duplicates and non-relevant studies excluded. The final selection, comprising 24 articles, focused on survival predictions through ML techniques. These studies, published mostly post-2019, included datasets ranging from 75 to 9,462 cervical cancer patients and up to 91,294 squamous cell samples. The most commonly applied ML models were Random Forest (RF), Neural Networks (NN), Support Vector Machines (SVM), Ensemble and Hybrid Learning, and Deep Learning (DL). The area under the curve (AUC) for these models ranged from 0.84 to 0.9875, demonstrating their strong predictive capabilities. Clinical patient records were the primary data source. Meta-analysis was performed on the extracted data using GraphPad Prism for descriptive statistics and One-Way ANOVA. No significant differences were found between group means, as evidenced by an R-squared value of 0.1459. This result indicates that the independent variable (year of study) explained only 14.59% of the variance in ML model performance. The study found that the use of ML models has increased over time, particularly with Convolutional Neural Networks (CNNs) such as the ResNet50 model, which demonstrated superior accuracy metrics, including over 90% accuracy for the ResNet152 variant. These findings suggest that integrating multi-dimensional data with ML models holds significant potential for improving survival predictions in cervical cancer patients. Future research is recommended to develop tailored ML algorithms with even higher predictive accuracy for cervical cancer survival.

Keywords: Cervical Cancer, Convolutional Neural Networks, Deep Learning, Ensemble Learning, Machine Learning, Predictive Accuracy, ResNet50, Survival Prediction

I. INTRODUCTION

A cancer that originates in the cervix is known as cervical cancer (CC) [1]. The cause is the abnormal growth of cells that can infiltrate or disperse throughout the body. There are usually no symptoms at the early stage. Other notable symptoms could be pain experienced during sex, pelvic pain or occasional bleeding of the vagina [1]. Although bleeding following sexual intercourse might not be alarming, it could suggest the potential presence of cervical cancer. The human papillomavirus (HPV) is usually the cause of most cervical cancers and it can come in different strains. HPV is a common infection that is transmitted through sex. Normally, the body immune system fights off the disease upon exposure, preventing any harm. However, in some few individuals, the virus persists for a longer period, transforming some of the normal cervical cells into cancerous ones.

According to National Cancer Institute, virtually all cervical cancer is caused by HPV. There are certain tests that are carried out to screen for cervical cancer. They are HPV, Histopathology as well as Visual Inspection after Acetic Acid application (VIA). If medical professionals are empowered to identify and remove precancerous cells, these routine tests can prevent most of the cases of the cervical cancer. Women who are screened infrequently or never screened have a high risk of cervical malignancy. Other risk factors are usage of pills for birth controls, smoking, having several sexual partners, having a weak immune system as well as early age sex – though with less significance. Cervical cancer risk is also influenced by genetic factors. Over the course of ten to twenty years, precancerous alterations known as cervical intraepithelial neoplasia usually led to cervical cancer. Squamous cell carcinomas account for 90% of cases of cervical malignancy while adenocarcinomas account for 10%, and few others with little percentage. Diagnosis is usually done by screening followed by a biopsy. Then next step is to perform medical imaging to see if the malignancy has spread.

Up to 90% of cervical cancer cases may be avoided by getting HPV vaccinations, which can offer defense against a range of two to seven high-risk variants of this virus [2] [3]. Guidelines advise ongoing, routine Pap screenings because there is still a chance of malignancy. Using condoms and having few or no sexual partners are two more preventative measures. Radiation therapy, chemotherapy, and surgery may be used in combination for treatment. The 5-year cancer survival rate in the United States of America is 68%. Nevertheless, the outcomes are significantly influenced by the timing of the cancer's diagnosis.

Cervical cancer is the fourth-ranked globally in terms of cancer incidence and cancer-related mortality among women [4]. In 2012, out of an estimate of 528,000 cervical cancer cases, 266,000 people died [4]. This represents almost 8% of all cancer cases and fatalities. Approximately 90% of fatalities and 70% of cases of cervical cancer occur in underdeveloped nations [4]. It is among the leading causes of cancer-related mortality in low-income countries, with an occurrence rate of 47.3 in every 100,000 women [5]. In advanced nations, the incidence of cervical cancer has drastically decreased due to frequency of screening schemes. The World Health Organization's (WHO) triple-intervention methods have been used to create anticipated scenarios for the worldwide decrease in mortality related to cervical cancer (particularly in countries with low-income) [5]. These scenarios are based on the premise that suggested preventative targets will be achieved.

Both ML and Deep Learning (DL) are used extensively in research. The former is far more effective because it requires segmentation and the acquisition of manually created features that make use of critical stages. In order to discover CC and improve the conventional testing procedure, Computer-Aided Diagnosis (CAD) techniques using Artificial Intelligence (AI) as the base, are typically explored.

This study's goal is to perform a Systematic Review and Meta-Analysis on Optimization of Screening Protocols for Cervical Cancer Through Machine Learning Models. PRISMA recommendations will be followed in the presentation of the results and any deviations from this protocol will be included in the report.

A. Rationale:

The goal of this project is to conduct a thorough review of the pertinent literatures in order to determine how machine learning models or algorithms might help forecast cervical cancer patients' survival through efficient screening and early disease identification. Finding the machine learning models that have performed the best in predictions is the ultimate objective.

B. Objectives:

The intent of this study is to undertake a Systematic Review and Meta-Analysis on Optimization of Screening Protocols for Cervical Cancer Through ML Models. This study will review the body of research on the use of ML models to predict the survival of patients with cervical cancer by utilising clinical or experimental data for efficient screening and early diagnosis. Important data will be obtained from the reviewed studies. Meta-analysis will be conducted on the data and the results will be analysed using descriptive statistics and performing one-way ANOVA using GraphPad Prism analytics tool. The results will be presented in accordance with PRISMA recommendations which will also include any deviations from the protocol.

Research issues below are addressed in the study using the PICOS framework:

i. Population: What attributes connect the cervical cancer research that employ ML algorithms to forecast patients' survival?
ii. Intervention: Which particular machine learning models are most frequently used in these investigations, and what kinds of experimental or clinical data form their basis?
iii. Comparison: Using the aforementioned data, how do different machine learning models compare against one another in terms of their prediction abilities?
iv. Outcome: Which of the many machine learning models proves to be the most accurate in predicting a patient's prognosis with cervical cancer, and what are the corresponding performance measures of each model?
v. Study Design: It is critical to evaluate the calibre and possible tendencies of research that have used ML models to predict CC survival. What biases might affect the results of these research, and how rigorous are they?

II. METHODS

An exhaustive search of the Scopus and PubMed databases for relevant materials was conducted in accordance with PRISMA recommendations. The search encompassed articles that are authored in English and published from January 1996 to February 2024. Keywords including "machine learning", "artificial intelligence", "deep learning", "cervical cancer", "cervical neoplasm", "screen*" and "protocol" were included in the search strategy.

A. Scope of the Review

Studies that employed the use of ML technique to forecast survival of patient in cervical cancer using experimental or clinical data are comprised in this systematic review.

B. Criteria for Eligibility

Eligibility requirements are derived from the PICOS framework:

Population: Research involving individuals with cervical cancer.

Interventions: Research using clinical data to estimate patients' survival through DL, ML and AI models.

Comparisons: Studies that compare the effectiveness of ML models with traditional approaches in predicting survival. Research using clinical data to evaluate patients' chances of survival using AI, ML and DL models.

Result/Outcomes: Studies disclosing machine learning model prognostic accuracy measures, including precision, sensitivity, specificity, area under ROC curve.

Research/Study Design: Clinical trials, observational studies, or simulation studies were taken into consideration.

C. Criteria for Inclusion

i. Studies that utilize machine learning methods in forecasting survival of patients with cervical malignancy.
ii. Research using cervical cancer patients as the main subject population
iii. Research evaluating the performance of different machine learning methods in comparison to the traditional methods of screening and forecasting survival of the cancer patients.
iv. English Publications.
v. Articles released between January 1996 to February.

D. Criteria for Exclusion

i. Studies that do not employ the use of ML methods to forecast patients' survival.
ii. Studies involving the main cohort of individuals with different forms of cancer.
iii. Studies not disclosing metrics for prediction model accuracy.
iv. Publications not written in English Language.
v. Unavailable full-text publications.
vi. Case reports, reviews, varieties of conferences and abstracts, editorial letters and meta-analytical reviews.

E. Data Source

The Scopus and PubMed databases were searched in order to find pertinent publications. The search technique combined keywords and medical terminology related to artificial intelligence, deep learning, screening, protocols, cervical cancer, and machine learning. To guarantee a thorough search, this approach was adapted to the requirements of each database.

F. Search Methodology

The search methodology was implemented resulting in capturing of relevant studies and literatures on cervical cancer and machine learning. The inclusion criteria include the following:

i. Original research on early detection prediction and patient survival with cervical cancer using machine learning algorithms.
ii. Research using clinical data and experimental data.
iii. Studies providing measurements for prediction model accuracy.
iv. Publications in the English language between January 1996 and February 2024. The entire electronic search strategy for the systematic review of "Optimisation of Screening Protocols for Cervical Cancer through Machine Learning Algorithms" was utilised to search the PubMed and Scopus databases.

Approach for utilizing Scopus Database: The method for finding relevant literature in Scopus database was used as follows:

TITLE-ABS-KEY (((optimiz*) AND (screen* OR analy*) AND ("cervical cancer" OR "cervical carcinoma" OR "cervical neoplasm") AND ("machine learning" OR "artificial intelligence" OR "AI" OR "deep learning") AND (algorithm* OR steps OR guideline OR program* OR protocol* OR procedure*))) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar"))

The query returned 52 documents.

Approach for utilizing PUBMED database: The method for finding relevant literature in Pubmed database was used as follows:

Search: (((((machine learning) OR (deep learning)) OR (artificial intelligence)) AND (cervical cancer)) AND ((protocol) OR (screening))) AND ((algorithm) OR (guideline)) Filters: Clinical Trial, Meta-Analysis, Randomized Controlled Trial, Review, Systematic Review

(((("machine"[All Fields] OR "machine s"[All Fields] OR "machines"[All Fields]) AND ("learning"[MeSH Terms] OR "learning"[All Fields] OR "learning"[All Fields] OR "learnings"[All Fields] OR "programming learnings"[MeSH Terms] OR ("programming"[All Fields] AND "learnings"[All Fields]) OR "programming learnings"[All Fields])) OR ("deep learning"[MeSH Terms] OR ("deep"[All Fields] AND "learning"[All Fields]) OR "deep learning"[All Fields]) OR ("artificial intelligence"[MeSH Terms] OR ("artificial"[All Fields] AND "intelligence"[All Fields]) OR "artificial intelligence"[All Fields])) AND ("uterine cervical neoplasms"[MeSH Terms] OR ("uterine"[All Fields] AND "cervical"[All Fields] AND "neoplasms"[All Fields]) OR "uterine cervical neoplasms"[All Fields] OR ("cervical"[All Fields] AND "cancer"[All Fields]) OR "cervical cancer"[All Fields]) AND ("protocol"[All Fields] OR "protocol s"[All Fields] OR "protocolized"[All Fields] OR "protocols"[All Fields] OR ("diagnosis"[MeSH Subheading] OR "diagnosis"[All Fields] OR "screening"[All Fields] OR "mass screening"[MeSH Terms] OR ("mass"[All Fields] AND "screening"[All Fields]) OR "mass screening"[All Fields] OR "early detection of cancer"[MeSH Terms] OR ("early"[All Fields] AND "detection"[All Fields] AND "cancer"[All Fields]) OR "early detection of cancer"[All Fields] OR "screen"[All Fields] OR "screenings"[All Fields] OR "screened"[All Fields] OR "screens"[All Fields])) AND ("algorithm s"[All Fields] OR "algorithmic"[All Fields] OR "algorithmically"[All Fields] OR "algorithmics"[All Fields] OR "algorithmization"[All Fields] OR "algorithms"[MeSH Terms] OR "algorithms"[All Fields] OR "algorithm"[All Fields] OR ("guideline"[Publication Type] OR "guidelines as topic"[MeSH Terms] OR "guideline"[All Fields]))) AND (clinicaltrial[Filter] OR meta-analysis[Filter] OR randomizedcontrolledtrial[Filter] OR review[Filter] OR systematicreview[Filter])

The query returned 67 documents.

G. Data Management

The documents retrieved from the databases of Scopus and that of PubMed were imported into Hubmeta software and then screened. The effective review of the 119 articles which satisfied the qualificatony requirements was made possible by Hubmeta software.

H. Study selection

To guarantee that only superior articles are featured, full text articles of those that satisfied the inclusion requirements or those in need of additional assessment were obtained.

I. Data extraction

The study's data collection concentrates on information such as patients' demography, size of sample, ML methods, clinical features, forecasting models, performance statistics among the data that have been extracted. The complete flow process was in accordance with PRISMA guidelines and it's shown in the Figure 1 below.

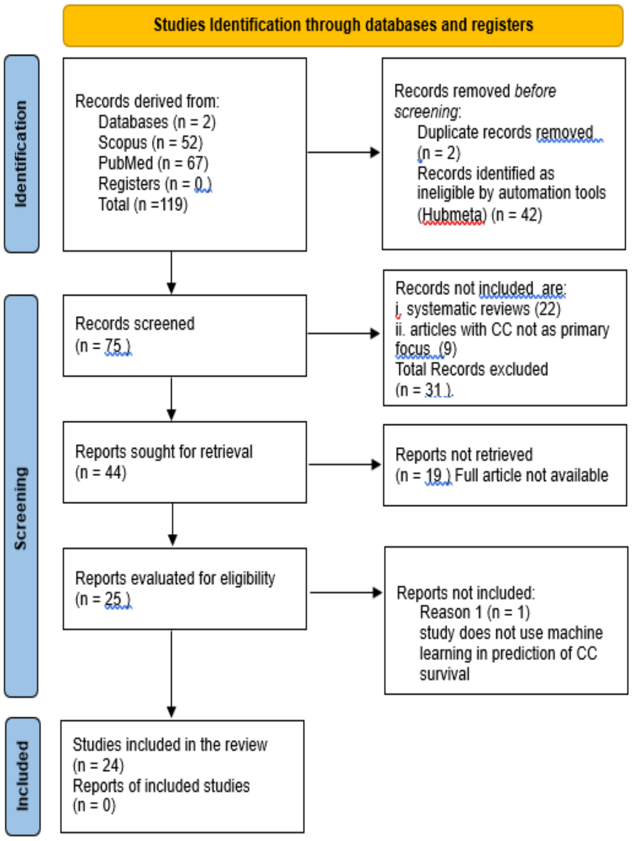

Fig 1. PRISMA Documentation Flowchart

J. Risk of bias

Articles that do not align with the selection criteria were filtered out. Also, articles that did not make cervical cancer their primary focus were also filtered out.

III. OUTCOME

This review considered the efficacy of various ML methods in early diagnosis and prognosis of cervical cancer alongside their utilization for forecasting survival rates among the cervical cancer patients. The use of performance measures and clinical data was the main focus. In all the models evaluated, many enhanced the prediction and screening of the cervical cancer. The primary metrics for evaluation are the predictive values of the machine learning models.

The search query generated 119 qualifying articles for review. Only 24 were considered appropriate for ultimate evaluation following utilization of criteria for inclusion and exclusion. The flowchart in Figure 1 illustrates the selection procedure utilized. A rigorous review process was followed to ensure quality articles were finally selected. Check for duplicates was done and articles abstract were deeply scrutinized against the qualification criteria for inclusion as well as exclusion. Final 24 studies shortlisted based on screening are summarised below in table of "Summary of Included Studies" (Table 1).

Table 1. Summary of Included Studies

1	Author/year/title/	Yu, Wenke;Lu, Yanwei;Shou, Huafeng;Xu, Hong'en;Shi, Lei;Geng, Xiaolu;Song, Tao 2022 [6] A 5-year survival status prognosis of nonmetastatic cervical cancer patients through machine learning algorithms
	Machine Model Used	Extreme Gradient Boosting (XGBoost), Random Forest (RF) Logistic Regression (LR), Support Vector Machine (SVM)
	Sample Size	Training cohort (No = 11,041) Validation cohort (No = 2,761)
	Dataset	Epidemiology, Surveillance, and End Results public database of the National Cancer Institute (2004 to 2016)
	Area Under Curve	N/A; Validation: 0.8365 (XGBoost)
	Biomarkers	Not specified
	Performance Metrics	ROC with AUCs. Decision Curve Analysis (DCA)
	Outcome	XGBoost outperformed other algorithms with AUC of 0.84 in training cohort and 0.8365 in validation cohort. The most significant variable was found to be the tumour stage [6].
2	**Author/title/year**	Hamdi, M.;Senan, E.M.;Awaji, B.;Olayah, F.;Jadhav, M.E.;Alalayah, K.M. 2023 [7] Analysis of WSI Images by Hybrid Systems with Fusion Features for Early Diagnosis of Cervical Cancer
	Machine Model Used	Deep Learning models (ResNet50, VGG19, GoogLeNet), Random Forest (RF), Support Vector Machine (SVM)
	Sample Size	Not specified
	Dataset	Cervical squamous cell dataset
	Area Under Curve	98.75%
	Biomarkers	Not applicable, as the study focuses on image analysis techniques rather than specific biomarkers
	Performance Metrics	Sensitivity: 97.4% - Accuracy: 99% - Precision: 99.6% - Specificity: 99.2%
	Outcome	Creation of automated whole-slide image (WSI) analysis models to aid in cervical squamous cell cancer early identification. The hybrid approach that combines RF and SVM algorithms with features from Deep Learning models (ResNet50-VGG19, VGG19-GoogLeNet, and ResNet50-GoogLeNet) is novel. Results indicate a notable enhancement in the performance of SVM and RF [7].
3	Author/year/title/	Kalbhor, M.;Shinde, S.V.;Jude, H. 2022 [8] Cervical cancer diagnosis based on cytology pap smear image classification using fractional coefficient and machine learning classifiers
	Machine Model Used	Discrete Coefficient Transform (DCT) and Haar Transform coefficients with seven different machine learning algorithms
	Sample Size	Not specified
	Dataset	Pap Smear Images (normal and abnormal)
	Area Under Curve	Not specified
	Biomarkers	Not specified
	Performance Metrics	Highest Classification Accuracy: 81.11% (achieved using DCT transform) – RF classifier achieved the best performance .
	Outcome	The study looks on the use of DCT Transform and Haar Transform Coefficients as characteristics in classification of cytology images. At 81.11%, the DCT Transform yields the best classification accuracy. The random forest classifier shows the overall best performance among the tested algorithms. The study aims to assist pathologists in providing accurate decisions based on cytology images, leveraging automated systems to improve efficiency and accuracy in cancer detection [8].
4	Author/year/title/	Dweekat, O.Y.;Lam, S.S. 2022 [9] Cervical Cancer Diagnosis Using an Integrated System of Principal Component Analysis, Genetic Algorithm, and Multilayer Perceptron
	Machine Model Used	Principal Component Analysis (PCA), Genetic Algorithm (GA) and Multilayer Perceptron (MLP).
	Sample Size	Not specified
	Dataset	Cervical cancer dataset
	Area Under Curve	Not specified
	Biomarkers	Not specified
	Performance Metrics	The PCA-GA-MLP integrated system that was suggested performs better than nine distinct categorization techniques. It outperforms previous methods in the area of diagnosis precision for Hinselmann, Biopsy as well as Cytology.
	Outcome	This study uses a combined system of The PCA-GA-MLP for forecasting cervical malignancy survival. GA provides prediction accuracy by optimising the hyperparameters of MLPs, and MLPs function as simulators within GA. Available factors are transformed by PCA and fed into MLP for model training. PCA-GA-MLP exhibits superior performance when compared to nine distinct categorization algorithms. This study presents a robust tool for early prediction of cervical cancer [9].
5	Author/year/title/	Wu, N.;Jia, D.;Zhang, C.;Li, Z. 2022 [10] Cervical cell extraction network based on optimized yolo
	Machine Model Used	Cell_yolo
	Sample Size	Not specified

	Dataset	BJTUCELL
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Detection accuracy, computational complexity
	Outcome	This model is better than popular network models like Faster_RCNN and YOLOv4. It solves a critical problem in detecting cervical malignance at the early stage by achieving high accuracy in segmenting cervical cells with significant overlap in microscopic images. [10].
6	Author/year/title/	Hunt, Brady;Fregnani, José Humberto Tavares Guerreiro;Brenes, David;Schwarz, Richard A.;Salcedo, Mila P.;Possati-Resende, Júlio César;Antoniazzi, Márcio;de Oliveira Fonseca, Bruno;Santana, Iara Viana Vidigal;de Macêdo Matsushita, Graziela;Castle, Philip E.;Schmeler, Kathleen M.;Richards-Kortum, Rebecca 2021 [11] Cervical lesion assessment using real-time microendoscopy image analysis in Brazil: The CLARA study
	Machine Model Used	Multi-Task Convolutional Neural Network (CNN) and High-Resolution Microendoscopy (HRME)
	Sample Size	1486
	Dataset	Not specified
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Sensitivity: 95.6% vs 96.2% (CIN3+), 91.7% vs 95.6% (CIN2+); Specificity: 56.6% vs 58.7% (CIN3+), 59.7% vs 63.4% (CIN2+) for HRME and similar to colposcopy in terms of sensitivity and specificity for detecting CIN2+ or CIN3+ (for CNN)
	Outcome	In order to detect CIN3+, HRME combined with morphologic image analysis demonstrated sensitivity and specificity that were comparable to colposcopy, but marginally less so for the detection of CIN2+. Algorithm based on neural network for HRME showed comparable performance to colposcopy in detecting CIN2+ and CIN3+, indicating HRME as a potential low-cost alternative for cervical cancer prevention [11].
7	Author/year/title/	Nour, M.K.;Issaoui, I.;Edris, A.;Mahmud, A.;Assiri, M.;Ibrahim, S.S. 2024 [12] Computer Aided Cervical Cancer Diagnosis Using Gazelle Optimization Algorithm With Deep Learning Model
	Machine Model Used	Computer Aided Cervical Cancer Diagnosis utilizing the Gazelle Optimizer Algorithm with Deep Learning (CACCD-GOADL)
	Sample Size	Not specified
	Dataset	Herlev benchmark dataset
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Superior outcomes over other methods
	Outcome	The CACCD-GOADL algorithm showed better results than alternative traditional techniques[12].
8	Author/year/title/	Kok, M. R.;Boon, M. E. 1996 [13] Consequences of neural network technology for cervical screening: Increase in diagnostic consistency and positive scores
	Machine Model Used	PAP-NET
	Sample Size	91,294 smears (25,767 conventional, 65,527 with PAPNET)
	Dataset	Not specified
	Area Under Curve	Not reported
	Biomarkers	Atypias squamous or glandular (ASCUC/AGUS), of unknown relevance.
	Performance Metrics	PAPNET performs better than the traditional screening methods.
	Outcome	Using neural network technology increased screening efficacy and improved the results of all cytotechnologists engaged [13].
9	Author/year/title/	Wong, L.;Ccopa, A.;Diaz, E.;Valcarcel, S.;Mauricio, D.;Villoslada, V. 2023 [14] Deep Learning and Transfer Learning Methods to Effectively Diagnose Cervical Cancer from Liquid-Based Cytology Pap Smear Images
	Machine Model Used	ResNet50V2 and ResNet101V2
	Sample Size	2,676 images
	Dataset	Liquid-based Pap smear images
	Area Under Curve	Not reported
	Biomarkers	Lesion level of cervical cancer (NI/LSIEL/HSIEL/SCC)
	Performance Metrics	Precision: 0.98 (HSIL and SCC), Accuracy: 0.97
	Outcome	The study created an image recognition model based on artificial intelligence to determine the Bethesda classification of cervical malignancy level in liquid-based Pap tests. Six tasks were carried out: choosing the dataset, augmenting the data, optimising the dataset, creating a model, assessing the model, and building the system. ResNet50V2 and ResNet101V2 methods were developed utilising Transfer Learning and Deep Learning protocols. Review showed that ResNet50V2 achieved better results with 0.98 precision for HSIL as well as SCC classification and 0.97 accuracy. ResNet50V2 model was developed and validated for higher performance [14].
10	Author/year/title/	Fekri-Ershad, S.;Alsaffar, M.F. 2023 [15] Developing a Tuned Three-Layer Perceptron Fed with Trained Deep Convolutional Neural Networks for Cervical Cancer Diagnosis
	Machine Model Used	Multi-Layer Perceptron (MLP) with Deep Features (based on ResNet-34, ResNet-50, and VGG-19)
	Sample Size	Herlev benchmark database
	Dataset	Pap smear images
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Accuracy: 99.23% (two-classes), 97.65% (seven-classes)
	Outcome	The study presents a combination method utilising a machine learning approach with deep learning-based feature extraction to diagnose cervical cancer. The feature extraction stage utilizes ResNet-34, ResNet-50, and VGG-19 deep networks, while the classification stage is based on a multi-layer perceptron (MLP) neural network. Based on innovative ideas, the amount of neurons layer hidden in the MLP is optimised. Both CNNs are trained on comparable images with the aid of Adam Optimizer. Evaluation on Herlev benchmark database showed the proposed method produced results in the two-class case of 99.23% accuracy and the seven-

		class case of 97.65% accuracy, outperforming baseline networks and existing methods [15].
11	Author/year/title/	A. Mansouri, R.;Ragab, M. 2022 [16] Equilibrium Optimization Algorithm with Ensemble Learning Based Cervical Precancerous Lesion Classification Model
	Machine Model Used	EOEL-PCLCCI (Equilibrium Optimizer with Ensemble Learning for Cervical Precancerous Lesion Classification on Colposcopy Images)
	Sample Size	Not specified
	Dataset	Benchmark dataset
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Not reported
	Outcome	The EOEL-PCLCCI method for classifying colposcopy images of cervical carcinoma is presented by this study. As a hyperparameter optimizer, it makes use of the Equilibrium Optimizer (EO) method and the DenseNet-264 architecture as the extractor feature. The classification method makes use of a Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) ensemble of weighted voting classifications. An evaluation of the EOEL-PCLCCI technique using simulation analysis on a benchmark dataset shows that it performs better than other deep learning models [16].
12	Author/year/title/	Nithya, B.;Ilango, V. 2019 [17] Evaluation of machine learning based optimized feature selection approaches and classification methods for cervical cancer prediction
	Machine Model Used	C5.0, RF, KNN, SVM and rpart.
	Sample Size	Not specified
	Dataset	Not specified
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Accuracy, prediction exactness
	Outcome	The study analyses cervical cancer risk factors using machine learning techniques in R. A range of feature selection methods are investigated in order to determine critical features for prediction. After this, an optimised model is developed. Classifier models that uses C5.0, RF, KNN, SVM and rpart algorithms are built and thoroughly evaluated. The complete accuracy of C5.0 and RF classifiers was shown to be satisfactory in detecting women that exhibited clinical indications of cervical carcinoma [17].
13	Author/year/title/	Ma, Y.;Liang, F.;Zhu, M.;Chen, C.;Chen, C.;Lv, X. 2022 [18] FT-IR combined with PSO-CNN algorithm for rapid screening of cervical tumors
	Machine Model Used	PSO-CNN
	Sample Size	Not specified
	Dataset	Serum samples of patients with cervical carcinoma, CIN I, CIN II, CIN III, and hysteromyoma were used.
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Accuracy (87.2%)
	Outcome	The PSO-CNN model outperformed classical Lenet, AlexNet, VGG16, and GoogLeNet DL models, achieving an accuracy of 87.2% in discriminating between the five types of samples. According to the study, this method may be used for the non-invasive, quick, as well as precise determination of people with cervical carcinoma. It may also be used for the intelligent diagnosis of other illnesses [18].
14	Author/year/title/	Zhu, X.;Li, X.;Ong, K.;Zhang, W.;Li, W.;Li, L.;Young, D.;Su, Y.;Shang, B.;Peng, L.;Xiong, W.;Liu, Y.;Liao, W.;Xu, J.;Wang, F.;Liao, Q.;Li, S.;Liao, M.;Li, Y.;Rao, L.;Lin, J.;Shi, J.;You, Z.;Zhong, W.;Liang, X.;Han, H.;Zhang, Y.;Tang, N.;Hu, A.;Gao, H.;Cheng, Z.;Liang, L.;Yu, W.;Ding, Y. 2021 [19] Hybrid AI-assistive diagnostic model permits rapid TBS classification of cervical liquid-based thin-layer cell smears
	Machine Model Used	AIATBS
	Sample Size	>81,000 retrospective samples, >34,000 multicenter prospective samples
	Dataset	Liquid-based thin-layer cell smear samples
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Sensitivity better than senior cytologists, high specificity, speed <180s/slide
	Outcome	The system achieves better sensitivity when compared to senior cytologists while maintaining high specificity and operates at a speed of less than 180 seconds per slide. [19].
15	Author/year/title/	Mazroa, A.A.;Ishak, M.K.;Aljarbouh, A.;Mostafa, S.M. 2023 [20] Improved Bald Eagle Search Optimization With Deep Learning-Based Cervical Cancer Detection and Classification
	Machine Model Used	IBESODL-CCDC
	Sample Size	Not specified
	Dataset	Cervical cancer dataset
	Area Under Curve	Not reported
	Biomarkers	Not reported
	Performance Metrics	Remarkable performance compared to other systems.
	Outcome	The algorithm employs a contrast enhancement process to improve image quality and used a modified LeNet model for feature extraction. The algorithm's performance is evaluated through comprehensive experiments, demonstrating remarkable performance compared to other recent systems [20].
16	Author/year/title/	Mosiichuk, V.;Sampaio, A.;Viana, P.;Oliveira, T.;Rosado, L. 2023 [21] Improving Mobile-Based Cervical Cytology Screening: A Deep Learning Nucleus-Based Approach for Lesion Detection
	Machine Model Used	RetinaNet with ResNet50 backbone
	Sample Size	Normal squamous cells of 31,698 and 1395 lesions
	Dataset	LBC samples digitalized with a portable smartphone-based microscope
	Area Under Curve	Not reported
	Biomarkers	Nuclei of cervical lesions.
	Performance Metrics	Class average precision, recall and F1 scores are 17.6%, 22.9%, and 16.0% respectively.

	Outcome	The proposed methodology improved on the best baseline that was reported in the documented research for identifying cervical lesions on microscopic images that were only obtained using mobile equipment connected to the µSmartScope device. Performance improvements were achieved through transfer learning, hyperparameter tuning, transfer learning and detected class adjustments as well as class score threshold optimization. The study reaffirms the potential of cervical cancer screening with AI-powered mobile applications, especially in places with limited access to medical resources [21].
17	Author/year/title/	Luo, Y.-M.;Zhang, T.;Li, P.;Liu, P.-Z.;Sun, P.;Dong, B.;Ruan, G. 2020 [22] MDFI: Multi-CNN Feature Integration for Diagnosis of Cervical Precancerous Lesions
	Machine Model Used	Multi-CNN decision feature integration
	Sample Size	Not specified
	Dataset	Cervical lesion dataset
	Area Under Curve	Not reported
	Biomarkers	Cervical lesions
	Performance Metrics	Not specified
	Outcome	The proposed method utilizes k-means algorithm for data preprocessing, cross-validation for model generalization, and transfer learning for fine-tuning two CNN models. The CNN decision results are integrated using the XGBoost algorithm. Experimental results show improved training of neural networks with the K-means data preprocessing method and better computer-aided diagnosis results with the proposed model meeting the needs of clinical diagnosis [22].
18	Author/year/title/	Battula, K.P.;Sai Chandana, B. 2023 [23] Multi-class Cervical Cancer Classification using Transfer Learning-based Optimized SE-ResNet152 model in Pap Smear Whole Slide Images
	Machine Model Used	Transfer learning-based optimized SE-ResNet152 model
	Sample Size	8838 images from Pap smear cells
	Dataset	SIPaKMeD dataset, CRIC dataset
	Area Under Curve	Not reported
	Biomarkers	Cervical cancer diseases
	Performance Metrics	Accuracy: 99.68%, Precision: 98.82%, Recall: 97.86%, F1-Score: 98.64%
	Outcome	For multi-class Pap smear image classification, the proposed method makes use of an optimised SE-ResNet152 model based on transfer learning. The Deer Hunting Optimization (DHO) algorithm optimizes the network's hyperparameters. The method addresses dataset imbalance by introducing cost-sensitive loss function during the classifier learning. Achieves superior results compared to existing approaches, demonstrating high performance statistics. The proposed method can potentially enhance automated preliminary diagnosis of cervical cancer diseases in hospitals and clinics [23].
19	Author/year/title/	Waly, M.I.;Sikkandar, M.Y.;Aboamer, M.A.;Kadry, S.;Thinnukool, O. 2022 [24] Optimal Deep Convolution Neural Network for Cervical Cancer Diagnosis Model
	Machine Model Used	Intelligent Deep Convolutional Neural Network for Cervical Cancer Detection and Classification (IDCNN-CDC)
	Sample Size	Herlev database
	Dataset	Images from Pap Smear
	Area Under Curve	Not reported
	Biomarkers	Cervical cancer
	Performance Metrics	Sensitivity, Specificity, Accuracy, F-Score
	Outcome	The IDCNN-CDC model utilizes Gaussian filter (GF) for preprocessing, Tsallis entrop using dragonfly optimization (TE-DFO) for segmentation, SqueezeNet for feature extraction, and weighted extreme learning machine (ELM) for classification of cervix cells in images from Pap smear. When compared to existing techniques, experimental results employing the Herlev database show improved performance in the key performance statistics. The proposed model exhibits promise for enhancing the use of biomedical imaging in detecting and classifying cervical carcinoma [24].
20	Author/year/title/	Tak, A.;Parihar, P.M.;Fatehpuriya, D.S.;Singh, Y. 2022 [25] Optimised feature selection and cervical cancer prediction using Machine learning classification
	Machine Model Used	Decision Trees
	Sample Size	Publicly available dataset from UC Irvine ML Repository
	Dataset	Hinselmann, Schiller, Cytology, Biopsy
	Area Under Curve	Not reported
	Biomarkers	Cervical cancer risk factors
	Performance Metrics	Accuracy, AU-ROC curve, Sensitivity, Specificity
	Outcome	SVM, KNN, Decision Trees and Ensemble Learning classifiers were trained on an imbalanced dataset of cervical carcinoma risk factors using oversampling methods. The Fine Gaussian SVM classifier achieved the highest accuracy for classifying Hinselmann (97.5%), cytology (62.5%), and biopsy (98%). Boosted trees achieved best result in classifying Schiller with 81.3% accuracy. [25].
21	Author/year/title/	Ma, Y.;Zhu, H.;Yang, Z.;Wang, D. 2022 [26] Optimizing the Prognostic Model of Cervical Cancer Based on Artificial Intelligence Algorithm and Data Mining Technology
	Machine Model Used	ChAMP methylation analysis, rbsurv, Cox regression
	Sample Size	Multi-type cloud information
	Dataset	Differentially methylated CpG sites (DMCs) of 14,419
	Area Under Curve	0.833
	Biomarkers	Methylated CpG sites
	Performance Metrics	AUC and Overall Survival (OS).
	Outcome	Constructed a prognostic model integrating four methylated CpG sites that predicted patient survival with an AUC of 0.833. In both training and validation datasets, low-risk and high-risk patient groups show significant differences in their risk scores in overall survival. The model was better at predicting survival time in patients with histological type and grade. When compared to gene expression data and other established models, the

		proposed model showed improved predictive accuracy [26].
22	Author/year/title/	Zhou, Z.;Maquilan, G.M.;Thomas, K.;Wachsmann, J.;Wang, J.;Folkert, M.R.;Albuquerque, K. 2020 [27] Quantitative PET Imaging and Clinical Parameters as Predictive Factors for Patients With Cervical Carcinoma: Implications of a Prediction Model Generated Using Multi-Objective Support Vector Machine Learning
	Machine Model Used	Multi-objective support vector machine (SVM) predictive model
	Sample Size	Stage IB2-IVA cervical carcinoma with 75 patients
	Dataset	PET imaging features and clinical parameters
	Area Under Curve	Locoregional Failure with AUC of 0.84 and Distant Failure with AUC of 0.75.
	Biomarkers	Clinical parameters (tumour size, nodal status, histology, age, race, stage). Imaging characteristics (12 textural, 9 intensity, 8 geometric, and 2 extra pre-treatment PET imaging features).
	Performance Metrics	Sensitivity, specificity, AUC, p-values
	Outcome	The model that used two imaging features (C+I) and clinical parameters had the highest performance in forecasting both locoregional failure (AUC of 0.84, specificity of 0.86 and sensitivity of 0.79) and distant failure (AUC of 0.75, specificity of 0.75 and sensitivity of 0.75), compared to models using only clinical parameters (C) or only imaging features (I) [27].
23	Author/year/title/	Ahmed, S.R.;Befano, B.;Lemay, A.;Egemen, D.;Rodriguez, A.C.;Angara, S.;Desai, K.;Jeronimo, J.;Antani, S.;Campos, N.;Inturrisi, F.;Perkins, R.;Kreimer, A.;Wentzensen, N.;Herrero, R.;del Pino, M.;Quint, W.;de Sanjose, S.;Schiffman, M.;Kalpathy-Cramer, J. 2023 [28] Reproducible and clinically translatable deep neural networks for cervical screening
	Machine Model Used	AI-based Deep Learning
	Sample Size	9462 women (17,013 images)
	Dataset	Integrated data
	Area Under Curve	0.89
	Biomarkers	HPV type
	Performance Metrics	Misclassification Rate: 3.4%. Sensitivity, Specificity Rate (% 2-Cl. D.)
	Outcome	Achieved high value Quadratic Weighted Kappa (QWK) of 0.86 with minimal % of 2-Class Disagreement [28].
24	Author/year/title/	Fernandes, K.;Chicco, D.;Cardoso, J.S.;Fernandes, J. 2018 [29] Supervised deep learning embeddings for the prediction of cervical cancer diagnosis
	Machine Model Used	Deep Learning Architectures
	Sample Size	Not specified
	Dataset	Individual medical records
	Area Under Curve	Top AUC = 0.6875
	Biomarkers	Not specified
	Performance Metrics	Accuracy, Sensitivity, Specificity
	Outcome	Achieved accurate prediction outcomes, surpassing the performance of earlier techniques like denoising autoencoders. Explored and validated clinical results from documented studies in medical research [29].

A. Findings

The 24 studies that fulfilled the requirements for inclusion criteria analysed between 75 to 9462 cervical cancer patients as well as squamous cells up to 91,294. The machine learning (ML) models applied in these studies comprises of neural networks, SVM, XGBOOST, decision trees, RF and deep learning algorithms developed by the researchers. The character of clinical data, experiments and method employed differed across the studies. The reported achievement statistics like prediction accuracy, AUC, sensitivity and specificity, showed that AUC values range between 0.68 and to 0.99, indicating moderate to high performance of the methods. Neural networks (especially ResNet152) produced the best accuracy of 99.68 when compared to other models. In the studies reviewed, neural network models (especially ResNet50) were more frequently used than other ML models, followed by Random Forest models and Support Vector Machine models. There were other Deep Learning Algorithms employed in the research that also recorded impressive performance metrics.

B. Meta-Analysis Report

The meta-analysis was carried out on the extracted data to analyse predictive capabilities of the ML models in the screening of cervical cancer over some time and make a prognosis using predictive analytics tool – GraphPad Prism. The Descriptive analysis and One-Way ANOVA (Analysis of Variance) was carried out on the data. ANOVA was considered suitable since we have multiple screening of the cervical cancer using ML algorithms over time with data spanning over six years.

How Meta-Analysis was performed in GraphPad Prism Analytic Tool:

i. Data Processing - There were three sets of data processed on GraphPad Prism. All the data were extracted from the studies reviewed. In the first set of data (see Table 2), the columns represent the different machine learning models while the rows represent time points (years). Each cell in the table represents the number of times the machine learning method was successfully used in screening of the patients to predict their survivability at that point. The second set of data contains the best performance accuracy of each machine learning model (see Table 5) among the studies reviewed. The third set of data is a summary of usage of the machine learning models (see Table 4.0).
ii. Selecting Analysis - Descriptive analysis was done for all the three sets of data. On the first set, one-way ANOVA was also performed on it (see Table 3 and Table 4).
iii. Visualization of Data - Visualizations of data, such as single and multiple bar charts as well as line graphs, were created in GraphPad Prism to illustrate trends in various machine learning methods over time. These visualizations aided in interpretation and presentation of findings. Figures 2.1 to 2.6 are individual machine learning model line charts generated from Table 2 on GraphPad Prism. Figure 3 is the performance metrics bar chart generated from Table 5 on the analytical tool while Figure 4 is the ML usage bar chart generated from Table 2 on the analytic tool using descriptive statistics.

Table 2. Data Extracted from Reviewed Studies

YEAR	XGBOOST	RF	CNN	SVM	DT	OTHERS
1996			1			
2018						1
2019		1				
2020			1	1	1	
2021	1		1		1	
2022	1	1	2	1		5
2023		1	6	1		1
2024						1

Table 3 Descriptive Statistics

DESCRIPTIVE STATISTICS	XGBOOST	RANDOM FOREST	CNN	SVM	DECISION TREE	OTHERS
Number of values	2	3	5	3	2	5
Minimum	1.000	1.000	1.000	1.000	1.000	1.000
Maximum	1.000	1.000	6.000	1.000	1.000	5.000
Range	0.000	0.000	5.000	0.000	0.000	4.000
Mean	1.000	1.000	2.200	1.000	1.000	1.800
Std. Deviation	0.000	0.000	2.168	0.000	0.000	1.789
Std. Error of Mean	0.000	0.000	0.9695	0.000	0.000	0.8000
Lower 95% CI of mean	1.000	1.000	-0.4919	1.000	1.000	-0.4212
Upper 95% CI of mean	1.000	1.000	4.892	1.000	1.000	4.021
Geometric mean	1.000	1.000	1.644	1.000	1.000	1.380
Geometric SD factor	1.000	1.000	2.189	1.000	1.000	2.054

C. *Visualized Data*

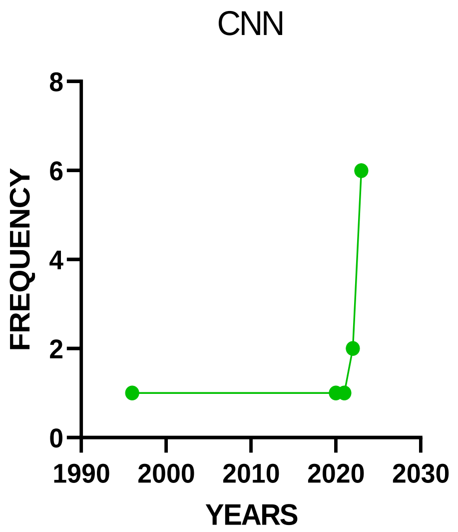

Fig 2.1 Visualization for CNN

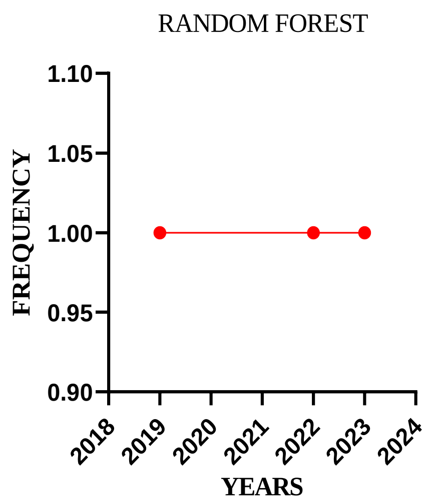

Fig 2.2 Visualization for Random Forest

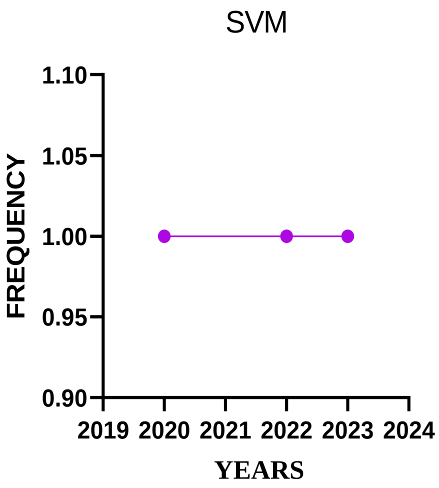

Fig 2.3 Visualization for SVM

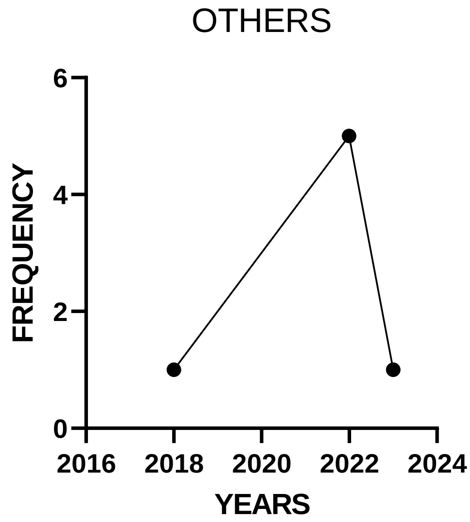

Fig 2.6 Visualization for Other Algorithms

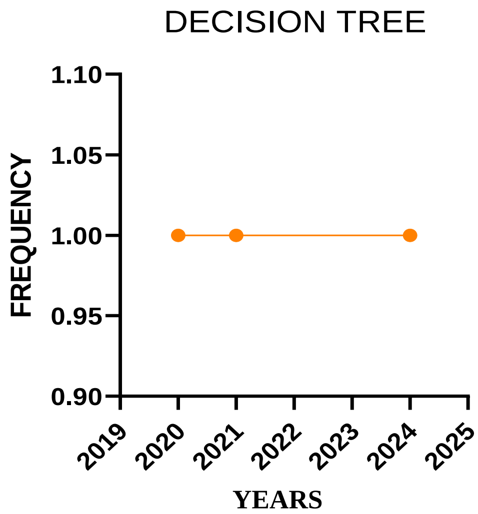

Fig 2.4 Visualization for Decision Tree

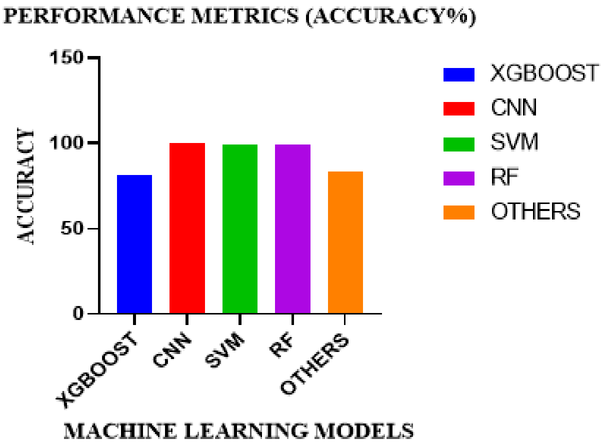

Fig 3.0

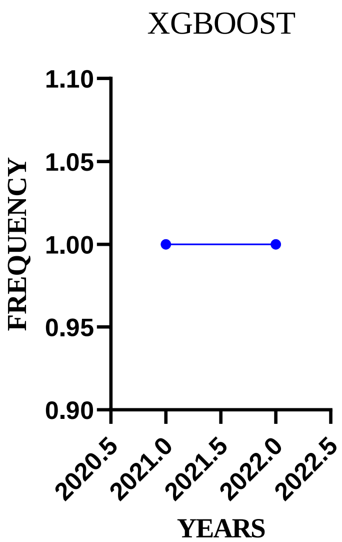

Fig 2.5 Visualization for XGBoost

Table 4 ANOVA Analysis

TABLE ANALYZED	DES				
Data sets analysed	A-F				
ANOVA summary					
F	0.4785				
P value	0.7865				
P value summary	ns				
Significant diff. among means (P < 0.05)?	No				
R squared	0.1459				
Brown-Forsythe test					
F (DFn, DFd)	0.4785 (5, 14)				
P value	0.7865				
Are SDs significantly	No				

different (P < 0.05)?					
ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	5.400	5	1.080	F (5, 14) = 0.4785	P=0.7865
Residual (within columns)	31.60	14	2.257		
Total	37.00	19			
Data summary					
Number of treatments (columns)	6				
Number of values (total)	20				

Table 5 Performance Metrics (Accuracy%)

MACHINE MODEL/ ACCURACY	XGBOOST	RF	CNN	SVM	OTHERS
%ACCURACY	81.51	98.75	99.68	98.75	83.3

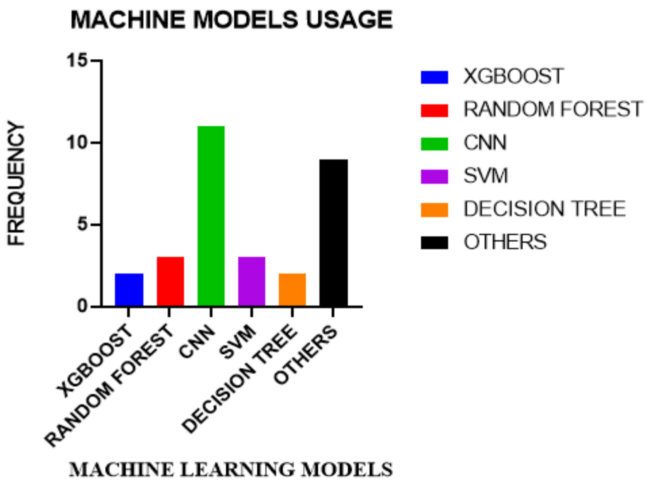

Fig 4.0

D. *Interpretation of Results*

To interpret the results, one may need to look at the main effect of the machine learning models on cervical cancer screening and their occurrences each year and over the years as well as interactions between them. Running ANOVA on GraphPad Prism provides the required information. Clinical relevance of the findings has to be determined by looking at the Significant levels of the result.

Using GraphPad Prism to process the data and analyze it with descriptive statistics and One-Way ANOVA allowed for the assessment of the machine learning models' efficacy over time as well as the facilitation of well-informed prognostic evaluations based on the processed data.

These findings do not provide any evidence that the group means differ significantly from one another.

ANOVA Summary:

- The F-statistic is 0.4785, and the associated p-value is 0.7865.
- Since the p-value is greater than 0.05, it shows that there is no substantial difference among the means of the group.
- An R-squared value of 0.1459 shows that the independent variable can only be responsible for about 14.59% of the variance in the dependent variable.
- Brown-Forsythe test also yields a non-significant result (p = 0.7865), indicating that the standard deviations are not significantly different across groups.
- These findings do not provide any evidence that the group means differ significantly from one another. The p-values for both the ANOVA and the Brown-Forsythe test are not less than or equal to 0.05, which statistically shows that there is no sufficient evidence to reject the null hypothesis of no differences among group means. Additionally, the R-squared value suggests that the independent variable is only responsible for a small proportion of the variance in the dependent variable.

E. *Synthesis of Results*

There are five machine learning models and Others analysed in the analytical tool (GraphPad Prism).

i. CNN – Convoluted Neural Network

Its usage starts from Year 1 (1996) and increases steadily until Year 7 (2023) with the highest count of six in Year 7 (2023).

ii. RF – Random Forest

Its usage starts from Year 3 (2019) and fluctuates in subsequent years. It's also used in Year 6 (2022) and Year 7 (2023).

iii. SVM – Support Vector Machine

Its usage starts from Year 4 (2020) and fluctuates in subsequent years. It's also used in Year 6 (2022) and Year 7 (2023).

iv. XGBOOST

Its usage only occurs twice in year 5 (2021) and year 6 (2022).

v. DECISION TREE

Its usage only occurs twice in year 4 (2020) and year 5 (2021).

There are other various ML models not explicitly mentioned. Their usage varies significantly across years, with the highest count of 5 in Year 6 (2022). There are 9 of such models.

Overall Trend

- The usage of ML models generally increases over time, indicating a growing adoption of ML techniques in screening of patients with cervical carcinoma.
- There is diversification in the choice of models, as indicated by the presence of multiple models in each year.
- There is preference for the use of Convoluted Neural Network (CNN) models as many studies show that it was frequently used.
- The use of CNN models grew in recent time because its reporting higher performance metrics over other models, especially ResNet50 model.
- The specific choice of models may vary each year, suggesting a dynamic landscape of machine learning applications

This analysis provides insights into the temporal evolution of ML model usage in the screening of cervical cancers, which can inform decision-making regarding model selection and resource allocation in future projects or research endeavours.

IV. DISCUSSION

The systematic evaluation of the application of ML to predict cervical cancer survival highlights both the potential and the problems of the technique. There are a number of elements that affect the models' accuracy and dependability. The outcomes are mostly dependent on the ML or algorithm that is selected. In addition, many research studies were excluded as they do not include the performance metrics in their reports.

The various models will produce different predictive results. So many factors can affect the results produced by each of the models, such as laboratory conditions, equipment handling, experience of research staff, imaging analysis equipment, cell classification etc. The more recent models like deep neural networks or combined approaches in Ensemble methods can offer better predictive capabilities. Recently, in the medical field, hybrid and ensemble models are being used more often, particularly for survival prediction. Random Forest (RF) and Extreme Gradient Boosting (XGBoost) models are examples of Ensemble Learning (EL) techniques. ML models are regularly improved in terms of computational characteristics, performance, generalizability, and accuracy through the use of hybrid and Ensemble methodologies in their development and optimisation.

In training ML models, the majority of studies have used clinical, imaging, and genetic data to predict survival with higher accuracy. The majority of publications that predicted cervical cancer survival using composite data were published after 2021.

Considering all of these findings, it is necessary to combine high-quality data, appropriate models, and cutting-edge approaches in order to enhance the predictive accuracy of cervical cancer survival predictions. In light of current developments in the field of artificial intelligence, more research is required to develop a very precise model for forecasting the survival of patients with cervical cancer.

V. CONCLUSION

The systematic review on the use of ML to predict cervical cancer survival reinforce both the potentials and challenges inherent in the process. As a result of their exceptional capabilities in feature extraction and selection, medical image processing, and pattern detection in data, ML algorithms have emerged as a major area of focus in research and development. In order to improve prediction accuracy, it is necessary to explore more sophisticated learning strategies, as highlighted in the discussion.

The majority of research publications published in the past several years on cervical cancer have employed ML algorithms to forecast the prognosis of individuals with cervical carcinoma. Applying ML approaches to heterogeneous multidimensional data may alter the forecasting of cervical cancer survival.

When predicting the prognosis of cervical cancer patients, machine learning outperforms conventional statistical techniques, but further research is required before it can be considered a standard.

REFERENCE

[1] PDQ Adult Treatment Editorial Board, "Cervical Cancer Treatment (PDQ®): Health Professional Version," *PDQ Cancer Information Summaries*, 2002, [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/26389493

[2] National Cancer Institute, "Human Papillomavirus (HPV) Vaccines What are human papillomaviruses ?," no. 10, pp. 1–9, 2017.

[3] N. P. Tran, C.-F. Hung, R. Roden, and T.-C. Wu, "Control of HPV infection and related cancer through vaccination.," *Recent Results Cancer Res*, vol. 193, pp. 149–71, 2014, doi: 10.1007/978-3-642-38965-8_9.

[4] S. McGuire, "World Cancer Report 2014. Geneva, Switzerland: World Health Organization, International Agency for Research on Cancer, WHO Press, 2015.," *Adv Nutr*, vol. 7, no. 2, pp. 418–9, Mar. 2016, doi: 10.3945/an.116.012211.

[5] K. Canfell *et al.*, "Mortality impact of achieving WHO cervical cancer elimination targets: a comparative modelling analysis in 78 low-income and lower-middle-income countries.," *Lancet*, vol. 395, no. 10224, pp. 591–603, Feb. 2020, doi: 10.1016/S0140-6736(20)30157-4.

[6] W. Yu *et al.*, "A 5-year survival status prognosis of nonmetastatic cervical cancer patients through machine learning algorithms.," *Cancer Med*, vol. 12, no. 6, pp. 6867–6876, 2023, doi: 10.1002/cam4.5477.

[7] M. Hamdi, E. M. Senan, B. Awaji, F. Olayah, M. E. Jadhav, and K. M. Alalayah, "Analysis of WSI Images by Hybrid Systems with Fusion Features for Early Diagnosis of Cervical Cancer," *Diagnostics*, vol. 13, no. 15, 2023, doi: 10.3390/diagnostics13152538.

[8] M. Kalbhor, S. V Shinde, and H. Jude, "Cervical cancer diagnosis based on cytology pap smear image classification using fractional coefficient and machine learning classifiers," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 20, no. 5, pp. 1091–1102, 2022, doi: 10.12928/TELKOMNIKA.v20i5.22440.

[9] O. Y. Dweekat and S. S. Lam, "Cervical Cancer Diagnosis Using an Integrated System of Principal Component Analysis, Genetic Algorithm, and Multilayer Perceptron," *Healthcare (Switzerland)*, vol. 10, no. 10, 2022, doi: 10.3390/healthcare10102002.

[10] N. Wu, D. Jia, C. Zhang, and Z. Li, "Cervical cell extraction network based on optimized yolo," *Mathematical Biosciences and Engineering*, vol. 20, no. 2, pp. 2364–2381, 2023, doi: 10.3934/mbe.2023111.

[11] B. Hunt *et al.*, "Cervical lesion assessment using real-time microendoscopy image analysis in Brazil: The CLARA study.," *Int J Cancer*, vol. 149, no. 2, pp. 431–441, 2021, doi: 10.1002/ijc.33543.

[12] M. K. Nour, I. Issaoui, A. Edris, A. Mahmud, M. Assiri, and S. S. Ibrahim, "Computer Aided Cervical Cancer Diagnosis Using Gazelle Optimization Algorithm with Deep Learning Model," *IEEE Access*, vol. 12, pp. 13046–13054, 2024, doi: 10.1109/ACCESS.2024.3351883.

[13] M. R. Kok and M. E. Boon, "Consequences of neural network technology for cervical screening: increase in

diagnostic consistency and positive scores.," *Cancer*, vol. 78, no. 1, pp. 112–117, 1996, doi: 10.1002/(SICI)1097-0142(19960701)78:1<112::AID-CNCR16>3.0.CO;2-2.

[14] L. Wong, A. Ccopa, E. Diaz, S. Valcarcel, D. Mauricio, and V. Villoslada, "Deep Learning and Transfer Learning Methods to Effectively Diagnose Cervical Cancer from Liquid-Based Cytology Pap Smear Images," *International journal of online and biomedical engineering*, vol. 19, no. 4, pp. 77–93, 2023, doi: 10.3991/ijoe.v19i04.37437.

[15] S. Fekri-Ershad and M. F. Alsaffar, "Developing a Tuned Three-Layer Perceptron Fed with Trained Deep Convolutional Neural Networks for Cervical Cancer Diagnosis," *Diagnostics*, vol. 13, no. 4, 2023, doi: 10.3390/diagnostics13040686.

[16] R. A. Mansouri and M. Ragab, "Equilibrium Optimization Algorithm with Ensemble Learning Based Cervical Precancerous Lesion Classification Model," *Healthcare (Switzerland)*, vol. 11, no. 1, 2023, doi: 10.3390/healthcare11010055.

[17] B. Nithya and V. Ilango, "Evaluation of machine learning based optimized feature selection approaches and classification methods for cervical cancer prediction," *SN Appl Sci*, vol. 1, no. 6, 2019, doi: 10.1007/s42452-019-0645-7.

[18] Y. Ma, F. Liang, M. Zhu, C. Chen, C. Chen, and X. Lv, "FT-IR combined with PSO-CNN algorithm for rapid screening of cervical tumors," *Photodiagnosis Photodyn Ther*, vol. 39, 2022, doi: 10.1016/j.pdpdt.2022.103023.

[19] X. Zhu *et al.*, "Hybrid AI-assistive diagnostic model permits rapid TBS classification of cervical liquid-based thin-layer cell smears," *Nat Commun*, vol. 12, no. 1, 2021, doi: 10.1038/s41467-021-23913-3.

[20] A. A. Mazroa, M. K. Ishak, A. Aljarbouh, and S. M. Mostafa, "Improved Bald Eagle Search Optimization with Deep Learning-Based Cervical Cancer Detection and Classification," *IEEE Access*, vol. 11, pp. 135175–135184, 2023, doi: 10.1109/ACCESS.2023.3337032.

[21] V. Mosiichuk, A. Sampaio, P. Viana, T. Oliveira, and L. Rosado, "Improving Mobile-Based Cervical Cytology Screening: A Deep Learning Nucleus-Based Approach for Lesion Detection," *Applied Sciences (Switzerland)*, vol. 13, no. 17, 2023, doi: 10.3390/app13179850.

[22] Y.-M. Luo *et al.*, "MDFI: Multi-CNN Decision Feature Integration for Diagnosis of Cervical Precancerous Lesions," *IEEE Access*, vol. 8, pp. 29616–29626, 2020, doi: 10.1109/ACCESS.2020.2972610.

[23] K. P. Battula and B. Sai Chandana, "Multi-class Cervical Cancer Classification using Transfer Learning-based Optimized SE-ResNet152 model in Pap Smear Whole Slide Images," *International Journal of Electrical and Computer Engineering Systems*, vol. 14, no. 6, pp. 613–623, 2023, doi: 10.32985/IJECES.14.6.1.

[24] M. I. Waly, M. Y. Sikkandar, M. A. Aboamer, S. Kadry, and O. Thinnukool, "Optimal deep convolution neural network for cervical cancer diagnosis model," *Computers, Materials and Continua*, vol. 70, no. 2, pp. 3297–3309, 2022, doi: 10.32604/cmc.2022.020713.

[25] A. Tak, P. Parihar, F. Singh, Y. S.-S. Medica, and undefined 2022, "Optimised feature selection and cervical cancer prediction using Machine learning classification," *scindeks.ceon.rs*, Accessed: Feb. 14, 2024. [Online]. Available: https://scindeks.ceon.rs/article.aspx?artid=2490-33292203205T

[26] Y. Ma, H. Zhu, Z. Yang, and D. Wang, "Optimizing the Prognostic Model of Cervical Cancer Based on Artificial Intelligence Algorithm and Data Mining Technology," *Wirel Commun Mob Comput*, vol. 2022, 2022, doi: 10.1155/2022/5908686.

[27] Z. Zhou *et al.*, "Quantitative PET Imaging and Clinical Parameters as Predictive Factors for Patients With Cervical Carcinoma: Implications of a Prediction Model Generated Using Multi-Objective Support Vector Machine Learning," *Technol Cancer Res Treat*, vol. 19, 2020, doi: 10.1177/1533033820983804.

[28] S. R. Ahmed *et al.*, "Reproducible and clinically translatable deep neural networks for cervical screening," *Sci Rep*, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-48721-1.

[29] K. Fernandes, D. Chicco, J. S. Cardoso, and J. Fernandes, "Supervised deep learning embeddings for the prediction of cervical cancer diagnosis," *PeerJ Comput Sci*, vol. 2018, no. 5, 2018, doi: 10.7717/peerj-cs.154.