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AI-Driven Ensemble Model for Predicting Multiple Quality Control Parameters in X-ray Diagnostic Radiology

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Abstract—*To maximize diagnostic radiology procedures with fewest risks to the patient and radiographers, a robust evaluation of other quality control (QC) parameters is necessary. Therefore, the purpose of this study is to evaluate the influence of other QC parameters on X-ray checks results i.e., kVp, reproducibility, mAs, and beam alignment using three AI-based approaches; Support vector machine (SVM), Artificial neural network (ANN), and eXtreme Gradient Boosting (XGBoost). kVp, reproducibility, mAs, beam alignment results and X-ray unit characteristics data from 10 X-ray centers were obtained and analyzed. The model's prediction results indicate that four X-ray units (i.e., 1, 2, 5, and 9) have excellent mAs linearity, higher reproducibility, and good alignment with prediction results > 0.9, followed by units 3 and 10 with very good linearity, reproducibility, and alignment as their forecasted results stood at > 0.85. However, units 4, 6, 7, and 8 require calibration as their kVp accuracy, mAs linearity, and beam alignment tolerance limits exceed the acceptable limits of; kVp = ±5%, mAs linearity coefficient (LC) ≤ 10%, and beam alignment ≤ 2% as their forecasted results stood at < 0.8 indicating a misalignment Also, the study found decay of X-ray machine, maintenance and servicing frequency, and number of X-ray examinations conducted per day to have significance influence on QC checks in the studied areas. The study concluded by suggesting regular calibration of radiological equipment and recommend areas for future research.*

Keywords— *Artificial intelligence, Quality control, kVp, mAs, Beam alignment, X-ray, Parameters.*

I. INTRODUCTION

Since the discovery of X-rays by Sir Wilhelm Conrad Roentgen in 1895, medical professionals and the general public have greatly benefited from their medical uses (Abd-Alla et al., 2019). Hernandez-Guzman et al. (2022), and Downie et al. (2023) in their works argued that extensive use of X-rays for patient diagnosis and treatment has led to an increase in radiation exposure. Studies have shown that radiological safety relies heavily on quality control. However, optimizing protection in medical exposure has received less attention compared to other applications of radiation sources due to the bulk of operations that result in medical exposure. The application of quality control program for X-ray diagnostic equipment is considered one of the most important issues in radiation protection, especially in medical radiation exposure control (Fazilov et al., 2024). Furthermore, to check the performance of X-ray machines, quality control procedures must be performed and this will take the highest priority over the other routine procedures since poor machine performance would lead to poor image quality. Therefore, a quality assurance program that covers all of these characteristics and procedures must be implemented. The goal of such a program is to obtain the best X-ray image with the minimum dose delivered to patient, and to minimize the rejection of poor X-ray images (Hussain et al., 2022; Veillette et al., 2024). Though ionizing radiation in diagnostic radiographs provides significant clinical benefits, but prolonged exposure of patients to radiation remains a concern for healthcare professionals. For instance, Steele et al. (2025), and Mammba et al. (2023) in their studies stressed that prolonged exposure to diagnostic imaging causes various health problems, such as increased cancer risk and acute radiation injury. The authors argued that these and other problems are usually due to inadequate quality control programs and non-compliance with radiation protection guidelines during practice. Although, few studies were conducted in the study area (i.e., Nigeria) with the view to evaluating the level of quality control program implementation in X-ray diagnostics radiology units, however, these studies possibly fall short in at least two aspects; i) number of control quality control parameters investigated. This is because the studies focused only on examining key quality control parameters such as kVp, mAs, entrance skin dose, focal spot size, and beam alignment (Aborisade, 2021; Ike-Ogbonna et al., 2020; Joseph et al., 2017) without considering other quality control parameters such as machine age and number of X-ray examinations conducted per day, and ii) the method employed i.e., conventional X-ray checks approaches such as reproducibility, linearity, and coefficient of variation (CV), and error% without employing other techniques e.g., artificial intelligence approaches due to their efficacy in modern research, especially in medical X-ray diagnostics (Almalki et al., 2021; Zanca et al., 2021). Thus, the purpose of this paper

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is to evaluate the influence of other quality control parameters on X-ray check results across 10 tertiary hospitals in the north-eastern part of Nigeria using 3 different Artificial intelligence (AI) based approaches. The rest part of the paper is structured as follows; Section 2 explains the materials and methods used in the research. Section 3 presents the results and discusses the findings. Finally, Section 4 summarizes the conclusions and suggests possible directions for future research.

II. Material and Methods

2.1 Evaluation Criteria

To achieve the study objectives, data from 10 different tertiary hospitals in the north-eastern part of Nigeria were assessed. For the purpose of data protection policy, the 10 X-ray radiology units utilized in the study were labelled as U1 - to – U10 (i.e., unit 1 –to- unit 10). The performance of the 10 X-ray machines was evaluated using 3 different AI algorithms; ANN, SVM, and XGBoost for predicting the influence of other quality control parameters on X-ray examination results. Details regarding the research evaluated X-ray machines across the studied X-ray units are offered in Table 1, encompassing; machine type, manufacturer, year of manufacturing, and installation year as per (Oglat, 2022). Additionally, all the studied X-ray machines across the units range from 2 -to-16 years, and the age effects on the machines are well documented. Also, operation guides for all the X-ray machines were available in all the studied X-ray units. Details regarding the research inputs data i.e., studied X-ray machines, kVp accuracy, reproducibility, mAs linearity, and beam alignment test results obtained from the studied X-ray units are offered in Table 1, 2, 3, 4, and 5.

As shown in Table 1, 3 X-ray diagnostic radiology units (i.e., unit5, units6, and unit8) use Siemens Healthineers machines, while units 4 and 7 utilize General Electric (GE) machines, and units 1 and 2 use Neusoft Medical Systems machines, and the remaining three units (i.e., units 3, 9 and 10) use Shimadzu Corporation, Philips and Hitachi Supria respectively. Details regarding the research-evaluated machines' specifications were captured directly from X-ray tube labels and the control panels of the studied X-ray machines.

TABLE 1: Specifications of the evaluated X-ray machines across the 10 units.

X-ray Units	Type of X-ray machine	Manufacturing Year	Installation Year	Inherent Filtration	Max Ma	Max KVp
U1	Neusoft Digital Mobile Radiography System	2020	2022	2.5mmA	500	80
U2	Neusoft Digital Mobile Radiography System	2021	2023	2.5mmA	640	120
U3	MobileDaRt Evolution MX8	2018	2019	2.7mmA	500	
U4	Definium 8000	2008	2010	2.5mmA	630	120
U5	Multix Impact	2019	2020	2.5mmA	620	110
U6	Ysio Max	2014	2017	2.5mmA	500	70
U7	Definium 8000	2010	2012	3.0mmA	620	100
U8	Siemens MULTIX Fusion	2015	2018	2.5mmA	610	90
U9	Philips DigitalDiagnost C90	2018	2022	3.0mmA	640	110
U10	Hitachi Supria X-ray System	2014	2019	2.5mmA	500	120

TABLE 2: Accuracy of the kVp measurement across the 10 X-ray units.

X-ray Unit	Set kVp 1	Measured kVp 1	Set kVp 2	Measured kVp 2	Set kVp 3	Measured kVp 3	kVp Error% (Mean)
1	70	71.1	90	91.4	110	111.5	1.63
2	70	73.6	100	94.2	120	115.3	5.13
3	70	71.2	90	91.6	110	111.9	1.76
4	70	73.8	100	94.6	120	115.8	5.41
5	70	71.4	90	91.9	110	112.3	1.94
6	70	73.7	100	94.5	120	115.5	5.26
7	70	70.9	90	91.2	110	111.4	1.33
8	70	71.2	80	91.5	110	111.8	1.73
9	70	73.6	100	94.3	120	115.2	5.17
10	70	71.4	90	91.8	110	112.2	1.93

TABLE 3: kVp reproducibility results

X-ray Unit	Set kVp	Measured kVp (Exposure 1)	Measured kVp (Exposure 2)	Measured kVp (Exposure 3)	Mean kVp	Standard Deviation (σ)	Coefficient of Variation (CV%)
1	70	70.2	69.8	70.1	70.03	0.20	0.28
2	120	126.3	125.1	126.0	125.80	8.86	7.04
3	90	90.2	90.0	90.1	90.10	0.11	0.13
4	80	74.6	73.8	74.4	74.27	4.62	6.21
5	90	90.1	89.8	90.2	90.03	0.18	0.20
6	100	95.0	93.5	94.6	94.37	5.92	6.28
7	70	70.2	69.9	70.0	70.03	0.16	0.23
8	90	90.2	89.8	90.1	90.03	0.26	0.29
9	120	127.0	125.8	126.7	126.50	8.64	6.83
10	70	70.4	69.8	70.3	70.17	0.15	0.21

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TABLE 4: mAs linearity coefficient (LC) results.

X-ray Unit	Set mAs	Measured mAs (Exposure 1)	Measured mAs (Exposure 2)	Measured mAs (Exposure 3)	Mean mAs	Standard Deviation (σ)	Linearity Coefficient (LC%)
1	10	10.2	9.8	10.1	10.03	0.09	0.89
2	30	55.2	53.7	54.0	54.30	5.57	10.26
3	50	50.2	50.0	50.1	50.10	0.09	0.48
4	63	112.7	110.8	111.9	111.80	13.80	12.33
5	50	50.1	49.8	50.2	50.03	0.12	0.58
6	10	11.0	10.2	10.6	10.60	1.17	11.02
7	10	10.3	10.0	10.1	10.13	0.05	0.53
8	60	99.8	100.3	100.1	100.07	0.26	0.91
9	10	11.0	10.4	10.7	10.70	1.07	10.33
10	50	50.1	49.7	50.2	50.00	0.16	0.63

TABLE 5: Difference between light field and radiation field.

X-ray Unit	L1 + L2 (%)	W1 + W2 (%)	Remarks
1	1.0	1.2	Pass
2	2.7	2.9	Fail
3	1.5	1.6	Pass
4	3.0	2.8	Fail
5	0.4	0.5	Pass
6	2.6	2.5	Fail
7	0.5	0.8	Pass
8	0.8	1.5	Pass
9	2.3	3.0	Fail
10	0.8	1.0	Pass

2.2 Artificial Intelligence (AI) Based Techniques

Research has shown that AI-based (ML) techniques exhibit superior performance in handling complex research areas such as engineering, computer science, and medical radiology due to their resilience, adaptability, and predictive power (Cavus et al., 2021a; Chang et al., 2022; Mohammed et al., 2024). Furthermore, in many cases, AI approaches can offer higher accuracy and lower complexity compared to other conventional methods. For instance, Gong et al. (2018) and Kamal et al. (2024) used an AI-based approach, specifically an Artificial neural network (ANN) to evaluate patient dose. The authors argued that integrating AI algorithms into imaging technology can enhance image quality, and reduce patient dose. Hence, the techniques offered greater precision and efficiency than the conventional evaluation methods. Therefore, this research utilized 3 different machine learning algorithms i.e., Artificial neural network (ANN), eXtreme Gradient Boosting (XGBoost), and Support vector machine (SVM), to obtain precise and reliable results regarding the influence of other quality control parameters (i.e., maintenance and servicing history, machine manufacturing year, number of X-ray examinations per day, radiographer's ability to operate the X-ray machine, and availability of operating manuals) on X-ray checks results.

2.3 Ensemble Method

The ensemble method is an AI-based approach that combines the prediction results of separate AI models to improve the performance of the research-reported model. Studies have also shown that "different approaches to a given problem can yield different results" (Cavus et al., 2022; Litjens et al., 2017). Currently, the use of collaborative approaches in medical sciences research has been proven to be efficient, and yield better results compared to a single modelling approach. Therefore, this study too utilized the approach (i.e., ensemble methods) to enhance the performance of the research separate AI models so that accurate and reliable results can be obtained. Algorithms of the research 3 AI based models (i.e., ANN, XGBoost, and SVM) were presented and explained in the following subsections

2.3.1 ANN Technique

ANN is an Artificial intelligence (AI)-based computational approach that simulates communication between neurons in the human brain. The technique is one of the most commonly employed "machine learning (ML) AI techniques" in medical sciences due to its intricate neural networks which are similar to the ones found in the human brain (Mohammed & Bulama, 2023). It provides computers the capability to learn the relationship between variables (i.e., input and output variables), for predicting or classifying the correlation among the variables, in our case other QC parameters and X-ray examination. As shown in Figure 1, the research ANN consists of 3 layers; Layer 1 (i.e., input layer) which contains the research inputs represented as $x_1 = x_n$ i.e., other QC parameters, X-ray tube efficiency, beam alignment, peak kilovoltage (kVp), and mAs, and Layer 2 is the weight assignment layer which is responsible for assigning weight to the inputs and mapping the inputs by adjusting synopsis weights until the best result is obtained, while Layer 3 is the output layer that present the network prediction or classification results. Algorithm of the research ANN approach is offered in Figure 1.

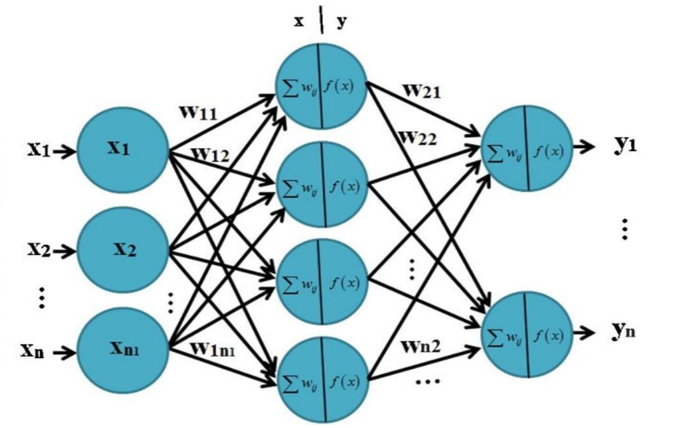

Figure 1: ANN Algorithm of the Study

The algorithm was implemented using Equation 1.

$$z = \sum_{i-1}^{n} wi, xi + b \quad (1)$$

Where: wi represents the network mapping weights, while xi denotes the study input features i.e., other QC parameters, and

QC checks using conventional X-ray measurement procedures and b represents the network bias which determines the model fitness level by adjusting the neuron's activation function. The network output (y), in this case, the classified effects of quality control parameters on the X-ray examinations is determined by applying the function activator to the biased summation. The output (y) results were achieved using Equation 2 as per(Garro et al., 2016).

$$y = \varphi(z) \quad (2)$$

2.3.2 XGBoost Technique

The "XGBoost technique" is one of the most widely utilized machine learning (ML) approaches due to its forecasting skills, and scalability in handling complex real-world problems. It gained considerable attention from scholars after it excelled at the "Kaggle's Higgs sub-signal detection competition" (Deng & Lin, 2022; Kanbul et al., 2024). Basically, XGBoost is an improved version of the GBDT method. It includes multiple decision trees and applications that are used in both regression and classification tasks. However, Zivkovic et al. (2022) and Thies et al. (2023) in their works stressed that XGBoost has several advantages compared to GBDT. The authors argued that "GBDT exclusively depends on a first-order Taylor expansion while XGBoost incorporates a second-order Taylor expansion in the loss function". Furthermore, the GBDT algorithm relies heavily on its normalization process to counteract overfitting and reduce model complexity, while the XGBoost uses its various tree functions as shown in Figure 2. The research XGBoost approach was implemented using Equation 3 as per (Song et al., 2020).

$$\hat{y} = \sum_{k=1}^{k} fk(x) \quad (3)$$

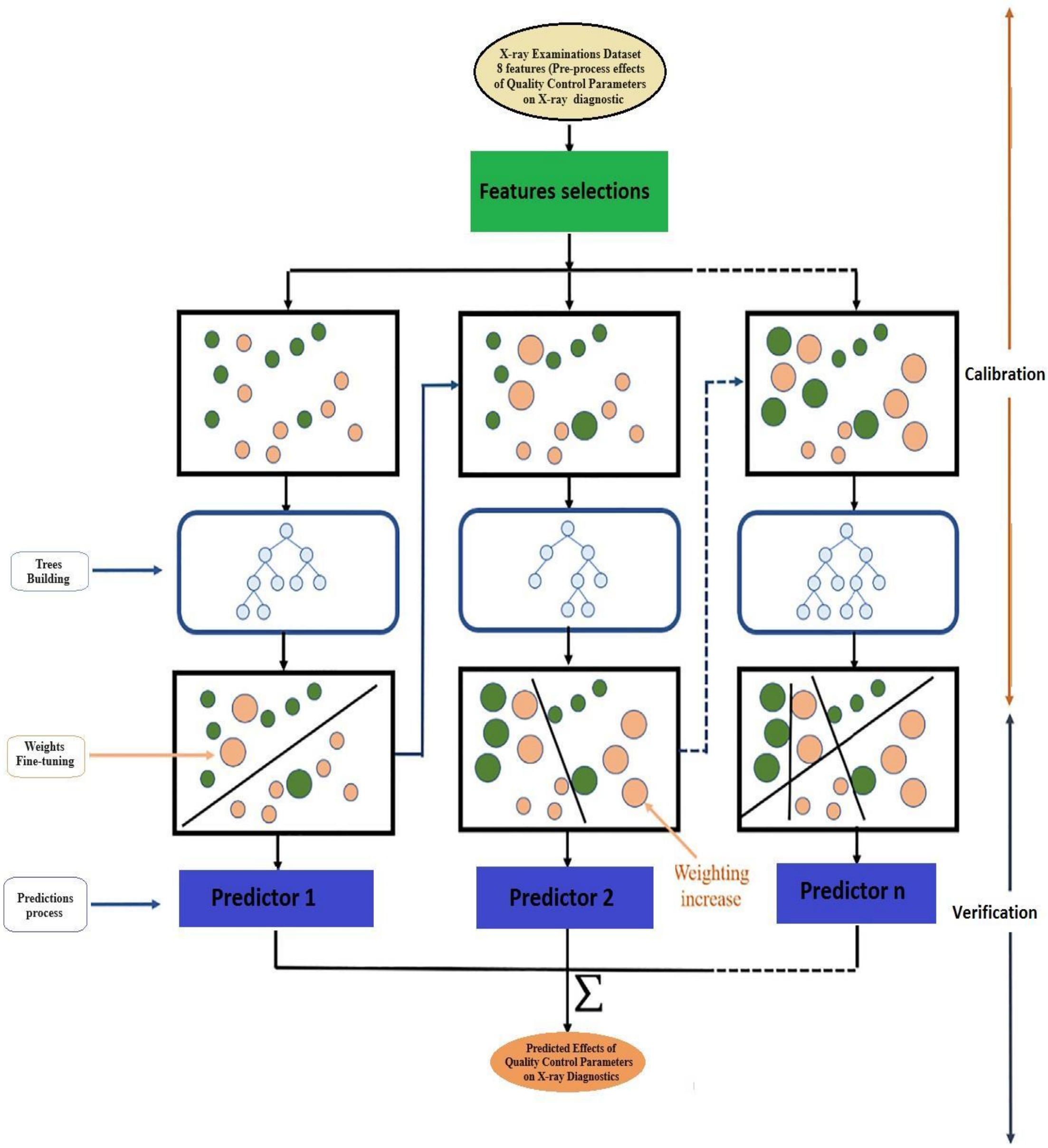

Figure 2: Structure of the research XGBoost technique

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2.3.3 SVM Technique

literature has shown that one of the foremost "machine learning (ML)" methods is the SVM technique as it robustly handles data uncertainty (Cavus et al., 2021b). The technique is normally used to set the optimal decision boundary (known as hyperplane) separating different datasets. The algorithm tries to find the ideal hyperplane by optimizing the distance (called margin) among different datasets. In contrast to other ML algorithms, SVM normally performs better in multidimensional problems, which makes it appropriate for situations where the sum of the features (dimensions) exceeds or equals the sample size. In SVM, the margin denotes the separation between the hyperplane and the closest observation points, also called "support vectors" (Wang et al., 2023). The main goal of SVM is to find the hyperplane that provides the largest margin value as this efficiently lessens the errors in the prediction process. The research SVM technique was achieved using Equation 4.

$$W^1\, x + b = \emptyset \qquad (4).$$

Where; *w* denotes the orthogonal hyperplane vector weights, *x* is the total number of inputs in the overall dataset, while *b* represents the bisector, and ∅ is the null-set sum in the dataset. Flow diagram of the research SVM technique is offered in Figure 3.

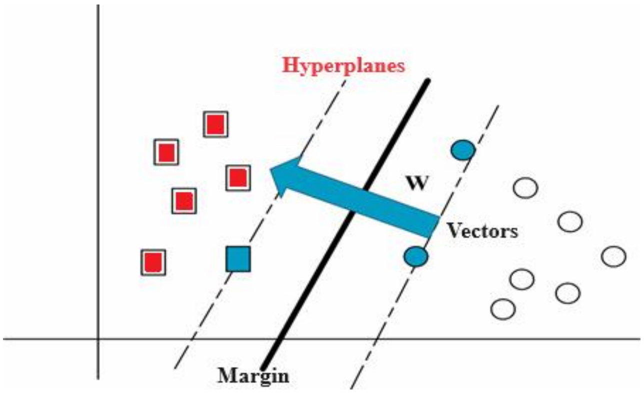

Figure 3. Workflow of the research SVM technique

2.4 Validation of the Study Adopted AI-based Techniques

The reason for the adoption of AI based techniques in research is due to their ability to produce reliable and precise results, a feat that is often difficult to achieve via conventional approaches without a deep and prior understanding of the area of study. However, due to the overfitting problem that affects the performance of different AI algorithms. The performance of these algorithms during training may not always reflect their performance during testing. This inconsistency is challenging as it can prevent researchers from obtaining precise and reliable results, especially on hidden datasets. To address this discrepancy and other issues, it is imperative to validate these algorithms. Several validation methods exist, such as "holdout validation, k-fold cross validation, and leave-one-out validation" to mention but a few (Kanbul et al., 2024). For this study, the fork-fold cross validation method was used due to its effectiveness as recommended by Awasthi and Goel (2022), using 4 evaluation indices; root mean square error (RMSE), coefficient of determination (R2), mean absolute percentage error (MAPE), and mean absolute error (MAE). The 4 metrics were explained using equations 5 to 8.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y^i - \hat{y}\right)^2}{\sum_{i=1}^{n} \left(y^i - \bar{y}\right)^2} \qquad (5)$$

$$MAE \; = \frac{\sum_{i=1}^{n} \left| N_{obs_i} - N_{pre_i} \right|}{n} \qquad (6)$$

$$RMSE \; = \sqrt{\sum_{i=1}^{n} \frac{\left(N_{obs_i} - N_{pre_i}\right)^2}{n}} \qquad (7)$$

$$MAPE \; = \frac{100\%}{n} \sum_{i=1}^{n} \frac{\left| N_{obs_i} - N_{pre_i} \right|}{N_{obs_i}} \qquad (8)$$

Flow diagram study of the research proposed AI based approach is offered in Figure 4, consisting of 5 key stages.

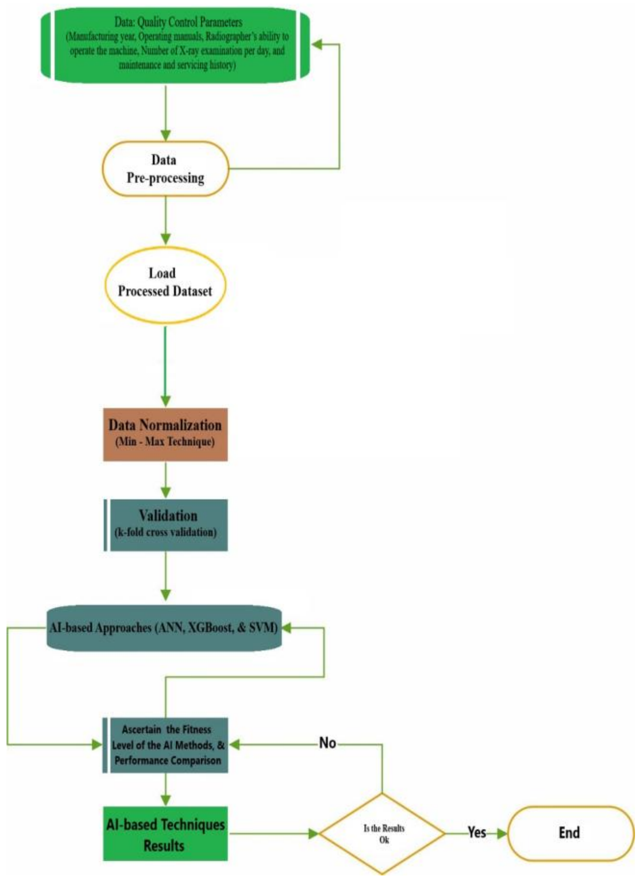

Figure 4. Flow diagram of the study proposed methodology

III. Results and Discussion

Having collected the research data from the 10 studied X-ray units. The collected data was processed using 3 artificial intelligence based methods; ANN, SVM, and XGBoost in order to obtain more precise results. The study AI based approach was divided into; i) Models validation and feature selections (i.e., X-ray unit characteristics), and ii) models prediction results regarding the influence of the study inputs on the research target i.e., quality control checks.

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3.1 Models Validation Results

To avoid overfitting issues associated with AI based models, the performance of the research utilized models was assessed using *RMSE*, R^2, *MAPE*, and *MAE*. Though, all the research 3 AI techniques perform well. However, it is evident that the ANN model achieved high prediction accuracy with $R^2 > 0.97$, *MAE* and *MAPE* < 7% in both testing and training, followed by the XGBoost technique with R^2 values of > 0.94, MAE, and MAPE < 13%. While the SVM came third. The performance of the ANN algorithm may not be unconnected with the model suitability in image-based research, especially in medical research like that of X-ray diagnostic radiology. In contrast, the forecasting skill of the SVM approach was ascetically low compared to both the ANN and XGBoost techniques, signifying the model's moderate forecasting skills regarding the impact of the research predictors i.e., X-ray unit characteristics such as; Machine manufacturing year, Availability of operating manuals, Radiographer's ability to operate the machine, Number of X-ray examination per day, and maintenance and servicing history on kVp and mAs checks results. The predictive skills of the research utilized AI approaches are offered in Table 6.

TABLE 6: Models validation results

	Training				Testing			
Algorithms	**R^2**	**MAE**	**RMSE**	**MAPE**	**R^2**	**MAE**	**RMSE**	**MAPE**
SVM	0.9001	14.6230	13.4231	13.0831	0.9121	13.6620	14.18932	12.0354
ANN	0.9732	6.8132	0.9869	2.8864	0.9802	6.0013	0.9964	2.0031
XGBoost	0.9468	11.0831	11.1278	12.2314	0.9527	9.6231	12.0332	12.1103

3.2 Relevant Features Selection Results

Examining relevant features in AI based approaches is very crucial in order to exclude irrelevant features and/or determine the importance of each input, in our case, the X-ray unit characteristics (i.e., Machine manufacturing year, Availability of operating manuals, Radiographer's ability to operate the machine, Number of X-ray examination per day, and maintenance and servicing history) which served as predictors of the study target i.e., quality control checks results across the studied 10 X-ray units. Therefore, the method was employed in this research to identify the most critical features among the unit chosen characteristics. The closer the value of the feature to one, the higher the impact of such feature, and the lower the feature value to one the lesser the significance of such feature on the research target. Determination of coefficient (*DC*) was used to assess the relevancy of each of the research-chosen unit characteristics using equation 9 as shown in Table 7.

TABLE 7: Relevant features selection results

Units characteristics	DC-values	Impact	Rank
Maintenance and servicing history	0.9824	High	1
Machine manufacturing year	0.9667	High	2
Number of X-ray examinations per day	0.9520	High	3
Radiographer's ability to operate the X-ray machine	0.9208	Moderate	4
Availability of operating manuals	0.8310	Low	5

As shown in Table 7, three of the research-chosen unit characteristics (i.e., maintenance and servicing history, machine manufacturing year, and number of X-ray examinations conducted per day) were found to be the most significant features among other parameters that influence quality control checks results in the research location. Also, the results indicate that the impacts of these three parameters on X-ray examination results were high compared to the last two parameters which have moderate and low impacts. Therefore, the first three parameters were ranked first, second, and third with the *DC* values of; > 0.98, > 0.96, and > 0.95 respectively. Though, the last two parameters (i.e., the radiographer's ability to operate the X-ray machine and availability of operating manuals) were ranked fourth and fifth respectively. However, they were still considered to be relevant on X-ray examination results. Thus, included among the research input parameters. Prediction results of the research employed AI based algorithms regarding the influence of other quality control parameters on X-ray examination results are offered in the following section.

3.3 Models prediction results

To obtain the research AI models prediction results, data collected from the studied X-ray units regarding the manufacturing year of the unit X-ray machines, availability of operating manuals, radiographer's ability to operate the installed X-ray machines, number of X-ray examinations performed per day in the unit, and servicing and maintenance frequencies (i.e., the chosen X-ray unit characteristics) were used as inputs or predictors of the research target i.e., quality control checks. Prior to the development of the study AI models i.e., "training" and "testing" of the models, the input data were normalized in the data pre-processing stage. Normalization of study input data simplifies mathematical operations in AI based modelling and simulation. Furthermore, the process helps minimize computation time while improving the accuracy of the models. Therefore, the research collated data were normalized to range between 0 -to- 1 using the "Max-Min" normalization approach. Precision, speeds, percentage error (%), and prediction results concerning the influence of study inputs i.e., other quality control parameters on X-ray examination results in the studied X-ray units. The models predicting results are presented in Figure 5, and Table 8. Where prediction > 0.9 indicates excellent linearity, higher reproducibility, and good alignment between the light field and radiation field, > 0.8 but less than 0.9 indicates very good linearity, reproducibility, and alignment, while < 0.8 indicates that the X-ray checks results exceed the acceptable limit.

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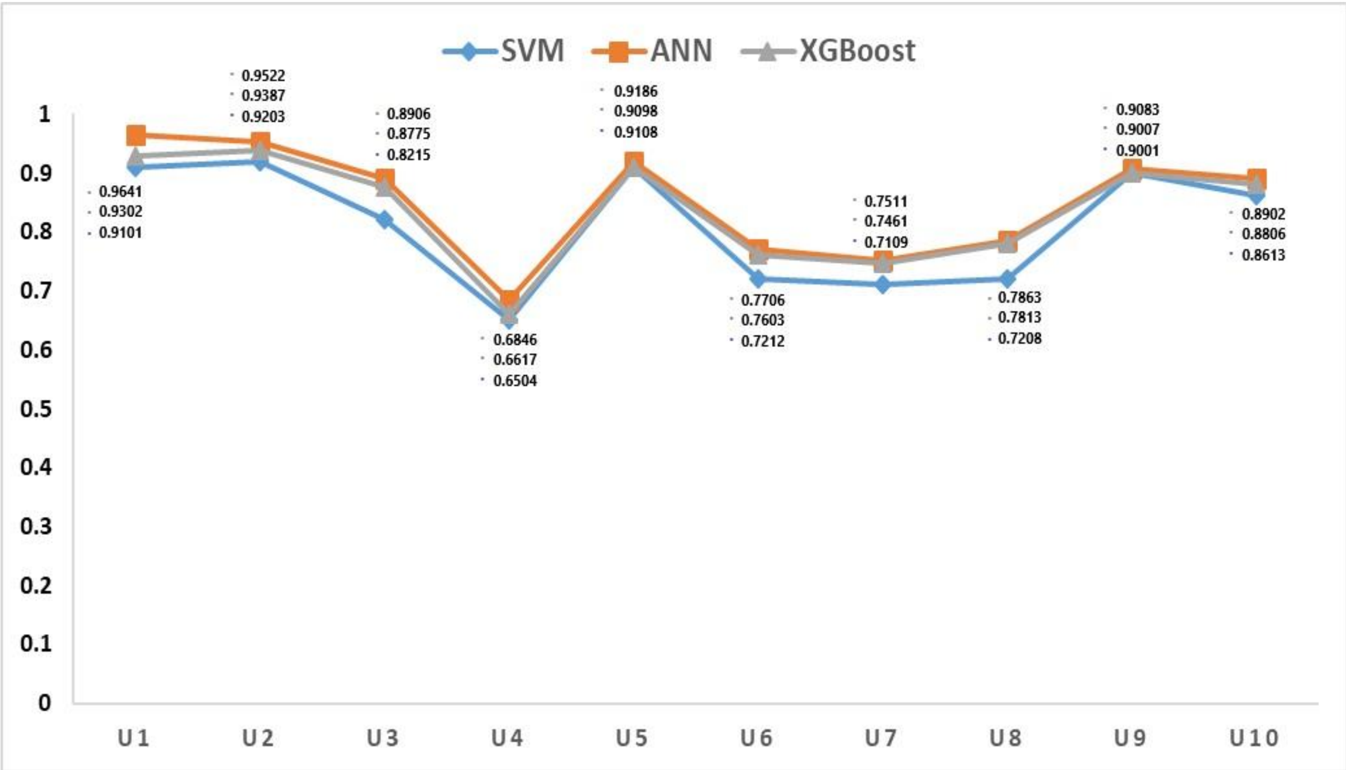

Figure 5: kVp, mAs, and bean alignment accuracy level predictions results of the research proposed AI model.

TABLE 8: Models precision results

MODELS	Calibration Precision	Calibration Speed	Calibration Time	Calibration Error%	Confirmation Precision	Confirmation Speed	Confirmation Time	Confirmation Error%
SVM	0.9080	~18 obs/sec	47.320 sec	0.0601	0.9110	~38 obs/sec	43.626 sec	0.03318
ANN	0.9303	~49 obs/sec	23.008 sec	0.0086	0.9586	~57 obs/sec	13.011 sec	0.0013
XGBoost	0.9189	~36 obs/sec	28.073 sec	0.0310	0.9203	~44 obs/sec	22.639 sec	0.0046

As shown in Figure 5, all the research proposed AI developed (ANN, XGBoost, and SVM) models predicted that four units (i.e., units 1, 2, 5, and 9) have an excellent mAs linearity, higher reproducibility, and very good alignment between the radiation field and the light field as all the models forecasting results were > 0.9. Also, the proposed models estimation results show that units 3 and 10 have very good linearity, reproducibility, and good alignment as the unit's forecasting results stood at > 0.85 but < 0.9. Conversely, the research models predicted that the kVp, mAs, and beam alignment examinations results conducted in units 4, 6, 7, and 8 exceed the accepted limit, signifying the volume of X-ray examinations conducted per day in those units, decay of the X-ray machines, and irregular maintenance and servicing activities carried out in those units. For the research models' precision skills, it can be said that all the research 3 developed AI algorisms have higher precision ability as all the models performed well in terms of the number of observations per second (obs/sec), and minimal erro% in both confirmation and training phases as shown in Table 4. Although, all the 3 models performed pretty well, however, the ANN technique outperformed the other techniques as the technique has a higher number of observations per second (~18 obs/sec and ~57 obs/sec), lesser error% (0.0086 and 0.0013), and higher precision (0.9303 and 0.9586) compared to the XGBoost and SVM techniques. The precision ability of the ANN technique may not be unconnected with the origin of the model i.e., from "human neurons" and the domain of the present research i.e., medical physics.

3.3 Discussion

In contrast to the majority of conventional X-ray checks studies, the study "artificial intelligence" (AI) developed models (SVM, ANN, and XGBoost) predicted that there is a strong correlation between quality controls checks and other parameters such as; maintenance and servicing history, machine manufacturing year, and number of X-ray examinations conducted per day. The results clearly indicate that accuracy and tolerance limits of X-ray check results i.e., such as kVp, reproducibility, mAs, scattered radiation, and beam alignment were significantly influenced by the decay of the X-ray machine, servicing and maintenance history, and the number of daily X-ray examinations conducted per day in the unit as all the 3 research utilized AI-based algorisms forecasted that for units (i.e., 1, 2, 5, and 9) have an excellent mAs linearity, higher reproducibility, and good alignment with prediction results > 0.9, followed by units 3 and 10 with a very good linearity, reproducibility, and alignment as their forecasting results stood at > 0.85 but < 0.9. However, the results show that the kVp and mAs accuracy levels, and beam alignment tolerance limits for units 4, 6, 7, and 8 exceed the acceptable limits as the units forecasted results were all < 0.8 indicating a misalignment and inconsistent kVp outputs in those units. Thus, the need for calibration of the units' X-ray machines. Also, findings of the research indicated that the manufacturing years for all the units (i.e., 4, 6, 7, and 8) that failed the kVp, reproducibility, mAs, and beam alignment checks ranged between 2008 –to- 2015 signifying the decay of the machines found in those units compared to the passing units. Therefore, it can be concluded that the manufacturing year of X-ray machine has a significant effect on the quality of X-ray checks, especially if the machine is not being serviced regularly. For the research features relevant selection results, it was discovered that three of the research employed other quality control parameters (i.e., maintenance and servicing frequency, manufacturing years of the X-ray machines, and the number of X-ray examinations conducted per day) have a high impact on the research target i.e., kVp, reproducibility, mAs linearity, and beam alignment checks results. The three features were ranked first, second, and third respectively, while the remaining two parameters (i.e., radiographer's ability to operate the X-ray machines, and availability of operating manuals) were found to have moderate and low impacts respectively. Thus, graded as the fourth and fifth.

3.4 Conclusion

In conclusion, this study analyzed and modeled the influence of other quality control parameters on X-ray examination results such as kVp, reproducibility, mAs accuracy, and beam alignment test across 10 X-ray units using 3 different "artificial intelligence" (AI) algorithms; SVM, ANN, and XGBoost. Findings of the study show that there is a strong association between other quality control parameters and X-ray checks as all the study employed AI techniques predicted the influence of the research inputs on X-ray examinations with greater precisions. Although, all the research AI algorithms performed well, but the ANN algorithm fared better than the other two algorisms i.e., SVM and XGBoost. Probably, the performance of the research AI based approaches, especially the ANN approach may not be unconnected with the algorithms precision skills compared to other conventional measurement procedures. Additionally, it the study results found regular maintenance and servicing of X-ray machines to be the most the most important determinants of kVp, reproducibility, mAs, and beam alignment accuracy and tolerance limits in all the studied X-ray facilities. Interestingly, this study set itself apart from other prior X-ray evaluation studies by introducing two significant novelties. First, unlike previous X-ray studies that usually utilized conventional kVp, reproducibility, mAs, and beam alignment measurement procedures, this research used a more robust approach i.e., AI-based techniques Second, the study AI approach looked at the influence of other quality control parameters on X-ray examinations results other than key parameters check results such as kVp output, mAs linearity, and alignment between light and radiation fields as seen in majority of prior quality control studies that used conventional measurement procedures. Nevertheless, this study contains limitations just like any other. It is limited to the particular AI techniques used, datasets obtained from the research 10 studied X-ray units, and the 5 chosen X-ray unit characteristics. Therefore, different AI techniques, X-ray unit characteristics, and more X-ray examination centres should be used in future studies to evaluate the influence of other quality control parameters on X-ray examinations for deeper understanding of the concept.

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