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An Artificial Neural Network-Based Quality Control Framework for Nigerian Manufacturing Industries

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Abstract

Manufacturing industries in developing economies face persistent challenges of inconsistent product quality, high defect rates, and the limited responsiveness of conventional inspection systems. This study develops and validates an Artificial Neural Network (ANN)-based quality control framework for Nigerian manufacturing industries. Three ANN implementations were examined across sectorally different companies: a supervised Multi-Layer Perceptron (MLP) binary classifier for Diaper Company and a Pharmaceutical Manufacturing Company, and an unsupervised Autoencoder for Paint Company where no historical quality labels existed. Models were evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and Matthews Correlation Coefficient (MCC). The pharmaceutical ANN achieved a ROC-AUC of 0.9098 and 92.5% accuracy. In the diaper case, the meta-classifier achieved perfect performance on the held-out study sample when highly informative sub-system diagnostic flags were incorporated as inputs, indicating the value of integrated machine signals rather than implying raw-sensor generalisation. The paint Autoencoder detected an anomalous batch with a reconstruction error 13.73 times the normal mean without any labelled training data. These results were synthesised into a five-stage, multi-modal quality control framework covering data infrastructure assessment, preprocessing, architecture selection, threshold calibration, and deployment. Overall, the study shows that ANN-based quality control is technically viable and practically accessible for Nigerian manufacturers using open-source tools, modest datasets, and context-appropriate modelling pathways.

Keywords: *Artificial neural networks; quality control; defect detection; Nigerian manufacturing; Industry 4.0.*

1.0 Introduction

Quality control (QC) is fundamental to manufacturing, ensuring that products conform to set standards and specifications [1]. Poor quality control leads to defective products, costly recalls, customer dissatisfaction, and damage to brand reputation [2, 3]. As global competition intensifies, the need for consistent product quality and process efficiency has never been more critical [4].

The evolution of QC mirrors technological progress. Early manufacturing relied on skilled craftsmen to inspect their own output [5]. The Industrial Revolution introduced mass production and professional inspection [6]. The 1920s brought statistical process control through Walter Shewhart's control charts, enabling manufacturers to monitor variability during production [7]. Post-war decades saw the rise of Total Quality Management (TQM) under Deming and Juran, followed by ISO 9000 standards that codified quality practices globally [6, 8]. Today, Industry 4.0 integrates cyber-physical systems, the Internet of Things (IoT), big data, and Artificial Intelligence (AI) into what is now called Quality 4.0 enabling real-time monitoring, predictive analytics, and adaptive quality management [9, 10].

Despite these advances, conventional QC methods remain dominant in many manufacturing environments, particularly in developing economies. End-of-line inspection, manual checking, and fixed-rule acceptance systems remain important in practice, but they are often labour-intensive, reactive, and slow. In many settings, defects are only discovered after production has already occurred, leading to rework, waste, delayed release, and avoidable financial loss [11]. In addition, conventional QC tools frequently assess variables one at a time or rely on predetermined thresholds, which makes them less effective when defects emerge from interacting process variables rather than from a single obvious deviation [12, 13]. As production lines generate larger and more heterogeneous data streams, these traditional approaches become increasingly difficult to scale efficiently [19, 20].

Artificial Neural Networks (ANNs) offer a compelling response to these limitations. Inspired by the human brain, ANNs learn directly from data, capture non-linear relationships between variables, and adapt to complex decision boundaries that are difficult to encode manually [14]. This makes them especially suitable for modern quality control problems, where product outcome may depend on the joint effect of machine settings, environmental conditions, material properties, and intermediate process signals rather than on any single feature in isolation [15, 16]. Across manufacturing sectors, ANN-based and broader AI-enhanced QC systems have been

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associated with stronger defect detection, faster analytical response, and reduced inspection burden when compared with purely manual or rule-based inspection workflows [17, 18, 19].

However, the practical implementation of ANN-based QC remains limited in developing countries such as Nigeria. Barriers include a lack of technical expertise, inadequate data infrastructure, and resistance to change from conventional practices [19]. A substantial proportion of existing research originates from developed countries and focuses narrowly on electronics, automotive, and semiconductor settings, limiting the transferability of findings to other manufacturing contexts [16]. Moreover, many published studies assume access to large, well-labelled datasets and mature digital infrastructure, conditions that many small and medium-sized manufacturers in developing economies do not yet possess [20]. Critically, there remains a notable absence of integrated implementation frameworks that show manufacturers how to move from their present data realities to workable ANN-based QC systems tailored to Nigerian industrial conditions.

This study addresses that gap. The aim is to develop and validate an ANN-based quality control framework for Nigerian manufacturing industries. The specific objectives are to: (i) design and implement an ANN model capable of identifying and classifying defects in manufacturing processes; (ii) evaluate the performance of the developed ANN model using real-world manufacturing data; (iii) validate the ANN model for reliability, accuracy, and robustness in defect detection; (iv) propose a practical framework for integrating ANN-based QC systems in Nigerian manufacturing industries; and (v) validate the proposed framework through case study implementation and performance assessment.

The study was conducted across three sectorally distinct Nigerian companies a diaper manufacturer, a paint company, and a pharmaceutical producer chosen because they represent diverse data environments and sectors where product quality directly impacts consumer safety and market competitiveness. The findings demonstrate that effective ANN-based quality control is technically viable and practically accessible for Nigerian manufacturers, without requiring large capital investment in proprietary software or specialised hardware [21].

2.0 Methodology

2.1. Research Design

This study follows a quantitative, experimental design grounded in applied machine learning. Real-world manufacturing data was collected from three Nigerian companies, and neural network models were built, trained, and evaluated empirically. Two modelling paradigms were employed depending on data availability: supervised binary classification was applied to the diaper and pharmaceutical datasets, where historical quality labels existed, while an unsupervised anomaly detection approach was used for the paint dataset, where no labelled defect records were available. This mixed-modelling strategy reflects the heterogeneous data environments of Nigerian manufacturing and ensures the framework remains practically adaptable across contexts [22, 20].

To ensure reproducibility and prevent data leakage, a fixed random seed (seed = 42) was applied throughout. All preprocessing transformations were fitted exclusively on training partitions, and stratified splits were used to preserve class distributions across subsets. The use of multiple evaluation metrics, rather than accuracy alone, reflects the asymmetric cost structure of quality control, where missed defects carry substantially greater operational and safety risk than false alarms [1, 23].

2.1.1. Data Sources and Description

Three distinct datasets were used, each sourced from the production records and quality control logs of the respective companies. Table 1 provides a comparative overview.

Table 1. Overview of the three manufacturing datasets used in this study

Dataset	Company	Records	Features	Label Type	Approach
Diaper QC	Diaper Company	5,000	24 / 30	Binary (PASS/FAIL)	Supervised MLP
Paint QC	Paint Company	717 (cleaned)	8	None (unlabelled)	Unsupervised Autoencoder
Pharma QC	Pharmaceutical Company	1,005	38	Engineered (ICH criteria)	Supervised MLP

The diaper dataset contained 5,000 production samples with 24 engineered features spanning process parameters (line speed, ambient temperature, humidity), material measurements (core weight, SAP uniformity, seal and cover integrity scores), mechanical properties (bond strength, elastic tension, tape adhesion), and contextual attributes (machine ID, shift, diaper size). A secondary model configuration incorporated six binary sub-system defect flags, extending the feature set to 30 inputs. The quality label was binary (1 = PASS, 0 = FAIL), with a class distribution

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of 86.2% PASS and 13.8% FAIL a profile characteristic of FMCG production environments where most output is conforming [23].

The paint dataset comprised 788 batch records from Paint company, capturing physicochemical attributes including pH, specific gravity, viscosity, fineness of grind, drying time, and temperature. No systematic PASS/FAIL quality labels had been maintained at the facility, making supervised learning inapplicable. After removing administrative identifiers and columns with excessive missing or not-applicable values, 717 records and eight informative features were retained for unsupervised modelling.

The pharmaceutical dataset contained 1,005 batch records from a cholesterol-lowering film-coated tablet product, sourced from a publicly available repository (Figshare). It included 55 columns covering raw material quality attributes, in-process tablet measurements, and final product quality indicators. Since no pre-existing quality label was available, a binary label (QC_PASS) was engineered from five final product attributes using internationally recognized pharmaceutical regulatory thresholds, as detailed in Table 2. Minimal missing values (0.07% of cells) were addressed via median imputation prior to modelling [24].

Table 2. Regulatory acceptance criteria used to engineer the pharmaceutical QC_PASS label

QC Attribute	Acceptance Criterion	Regulatory Basis
Dissolution average	≥ 80%	USP / Ph. Eur. Stage 1
Dissolution minimum (unit)	≥ 75%	Individual unit lower limit
Total impurities	≤ 0.50%	ICH Q3A
Residual solvent	≤ 0.10%	ICH Q3C Class 2
API content uniformity	90% – 110%	ICH Q6A

A batch was assigned QC_PASS = 1 only if all five criteria were simultaneously satisfied; failure on any single criterion resulted in QC_PASS = 0. This yielded 887 PASS (88.3%) and 118 FAIL (11.7%) batches.

2.2. Software and Computational Tools

All modelling and analysis were conducted in Python 3.12 within Jupyter Notebooks on Google Colaboratory (GPU-enabled, CUDA 12.8). The key libraries used were: Scikit-learn 1.6.1 for the MLP classifiers, preprocessing pipelines, and evaluation metrics; PyTorch 2.10.0 for the Autoencoder; Pandas 2.2.2 and NumPy 2.0.2 for data manipulation; and Matplotlib 3.7.1 and Seaborn 0.13.1 for visualisation.

2.3. Data Preprocessing

Each dataset underwent a tailored preprocessing pipeline reflecting its unique characteristics. A strict no-leakage principle was maintained throughout: any transformation estimated from data including scaling parameters and imputation medians was fitted exclusively on the training partition and then applied to validation and test sets.

For the diaper dataset, administrative columns were removed and two model configurations were constructed. Model A retained 12 continuous sensor features plus one-hot-encoded categorical variables, yielding 24 inputs. Model B added six sub-system defect flags for 30 total inputs. A stratified 70/15/15 train-validation-test split preserved the class ratio across all partitions. To address the 86.2%/13.8% class imbalance, the minority FAIL class was oversampled within the training set only using random oversampling with replacement, reaching approximately one-half of the PASS count (3,017 PASS: 1,508 FAIL). All features were then standardized using StandardScaler fitted on the oversampled training data [23].

For the paint dataset, six columns were removed, two administrative identifiers and four columns with high proportions of 'NOT APPLICABLE' entries. Remaining missing values were handled via listwise deletion, reducing the dataset from 788 to 717 records. Because the model was developed as an unsupervised feasibility study in a context with no historical labels, standardisation was applied to the cleaned dataset before partitioning into a 70/15/15 split. This choice does not leak class labels, since none existed, but it should be interpreted as part of a proof-of-concept anomaly-detection pipeline rather than as a definitive deployment benchmark.

For the pharmaceutical dataset, the seven quality output columns used to construct the QC label, along with ten administrative identifier columns, were excluded from the feature matrix to prevent data leakage. Six string-typed columns were coerced to numeric, yielding 38 input features. Missing values were handled with median imputation using SimpleImputer. A stratified 80/20 split yielded 804 training and 201 test samples. Rather than oversampling, class imbalance was addressed through inverse-frequency class weights, assigning a weight of 4.277 to the FAIL class and 0.566 to PASS directly penalising missed defects during gradient descent [25].

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2.4. Neural Network Architectures

Three distinct architectures were designed, each selected based on the data characteristics and quality control requirements of the corresponding manufacturing context.

The diaper MLP classifier was implemented using Scikit-learn's MLPClassifier. Both Model A and Model B shared the same three-layer architecture: Input(n) → Dense(128, ReLU) → Dense(64, ReLU) → Dense(32, ReLU) → Output(1, Sigmoid), where n = 24 for Model A and n = 30 for Model B. Model A was designed to learn from raw process and contextual variables alone, while Model B explicitly functioned as a meta-classifier by integrating six binary sub-system defect flags generated by upstream machine checks. These flags were treated as available diagnostic inputs rather than as variables derived from the final qc_label. L2 regularisation was applied to reduce overfitting risk [26].

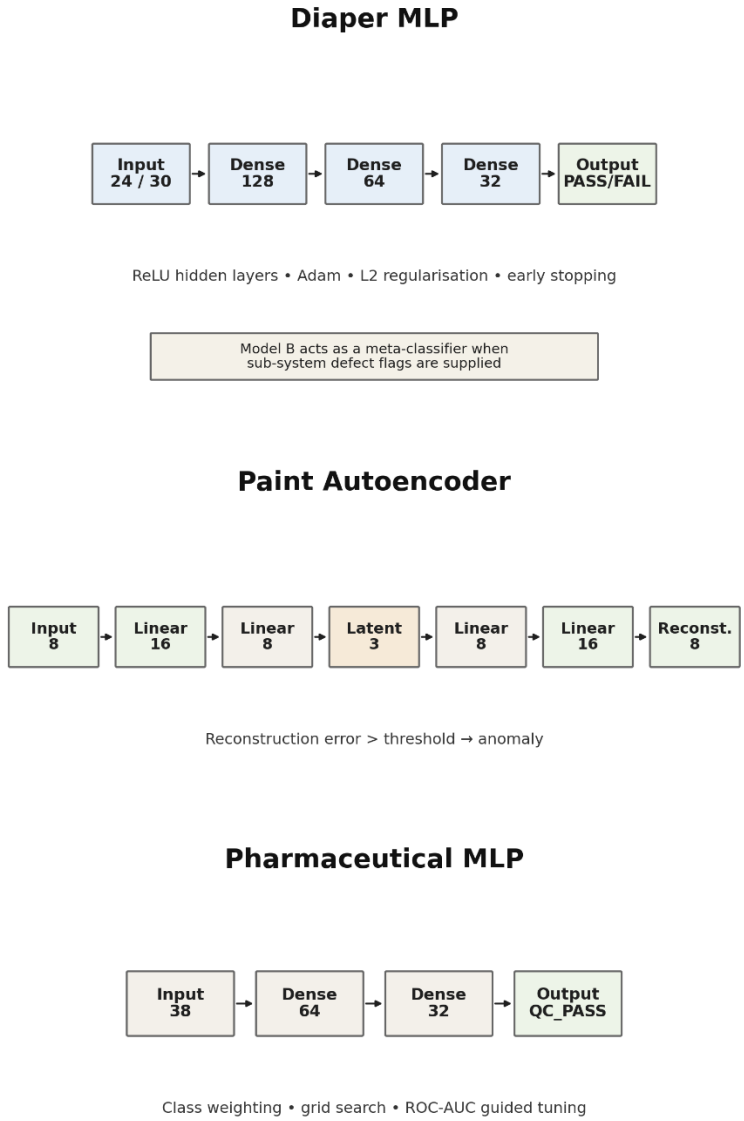

Figure 1. ANN architectures used in the study: diaper MLP, paint Autoencoder, and pharmaceutical MLP

The paint Autoencoder was implemented in PyTorch for unsupervised anomaly detection. The encoder compressed the eight standardised input features through three linear layers to a three-dimensional bottleneck: Input(8) → Linear(16, ReLU) → Linear(8, ReLU) → Linear(3). The decoder symmetrically reconstructed from this latent code: Linear(3) → Linear(8, ReLU) → Linear(16, ReLU) → Linear(8). The model contained 619 trainable parameters. The deliberate three-neuron bottleneck forces the network to retain only the most essential regularities of normal batches, so anomalous batches produce elevated reconstruction error at inference. Any batch whose reconstruction error exceeded the 99th percentile of the validation set distribution was flagged as anomalous.

The pharmaceutical MLP classifier used a baseline architecture of Input(38) → Dense(64, ReLU) → Dense(32, ReLU) → Dense(16, ReLU) → Output(1, Sigmoid). Following hyperparameter optimisation, the final model used two hidden layers (64, 32) with L2 regularisation alpha = 0.0001 and learning rate = 0.001 [27].

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2.5. Model Training Procedures

Both diaper models were trained using the Adam optimiser [27] with an initial learning rate of 0.001, mini-batch size of 32, and L2 regularisation (alpha = 0.001). Early stopping with a patience of 20 epochs was applied, monitoring validation accuracy with a maximum of 300 epochs. Model A converged at epoch 85 with a validation accuracy of 91.31%; Model B converged at epoch 22.

The paint Autoencoder was trained for 100 epochs using Adam (learning rate = 0.001) and Mean Squared Error (MSE) loss, with a mini-batch size of 16. Training and validation losses were monitored at each epoch for overfitting. The final training MSE was 0.1791 and validation MSE was 0.2512, yielding a train-validation gap of 0.0722 indicating controlled, non-severe overfitting.

The baseline pharmaceutical model was trained with Adam (learning rate = 0.001), alpha = 0.001, batch size 32, and early stopping (patience = 20, max 500 epochs), converging at epoch 38. Hyperparameter optimisation was then conducted using five-fold stratified GridSearchCV, evaluating 18 combinations across hidden layer sizes [(64,32), (64,32,16), (128,64,32)], L2 strengths [0.0001, 0.001, 0.01], and learning rates [0.001, 0.0005], scored by ROC-AUC. The optimal configuration hidden layers (64, 32), alpha = 0.0001, learning rate = 0.001 achieved a mean cross-validation ROC-AUC of 0.9055, consistent with the recommendation by Sajitha and Priya [26] and Nagy et al. [24] that systematic hyperparameter search is essential for maximising ANN performance on imbalanced pharmaceutical datasets.

2.5.1. Decision Threshold Optimisation

For the diaper models, the default decision threshold of 0.5 was not assumed optimal. Given the safety implications of releasing defective infant products, threshold tuning was performed on the validation set by evaluating FAIL F1-score across thresholds from 0.05 to 0.95 in steps of 0.01. The optimal threshold was 0.92, reflecting the asymmetric cost structure of quality control in infant hygiene products. Threshold tuning was conducted exclusively on the validation set to avoid contaminating the test set [23].

For the pharmaceutical model, the class-weight balancing strategy was the primary mechanism for addressing cost asymmetry, and the default 0.5 threshold was retained. For the paint Autoencoder, the anomaly threshold was set at the 99th percentile of the validation set reconstruction error distribution (threshold = 2.0048), ensuring 99% of normal batches fell below it.

2.6. Model Evaluation Metrics

Supervised models were evaluated on held-out test sets using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis. Recall on the FAIL class was prioritised as the most operationally critical metric, since undetected defects expose consumers to risk and incur downstream costs [29]. The Matthews Correlation Coefficient (MCC) was additionally reported for the pharmaceutical case study, as it provides a balanced scalar metric robust to class imbalance and is recommended for binary classification in pharmaceutical datasets [25]. For the diaper case, Average Precision (AP) from the precision-recall curve was also computed, providing a more informative summary than ROC-AUC under severe class imbalance [28].

For the paint Autoencoder, where ground-truth labels are unavailable, performance was assessed through the per-sample reconstruction error distribution, the anomaly-to-normal reconstruction error ratio, and a latent space projection visualising where flagged batches fall relative to the normal production cluster.

2.7. Feature Importance Analysis

Feature importance was assessed using approaches appropriate to each model type. For the diaper MLP, the mean absolute values of input-layer weights connecting each feature to the first hidden layer were used as a first-order indicator of feature relevance [26]. For the pharmaceutical ANN, permutation importance was computed (n_repeats = 20, scored by ROC-AUC), measuring the drop in model AUC when each feature's values were randomly shuffled a model-agnostic method that provides statistically reliable estimates [30]. For the paint Autoencoder, per-feature reconstruction errors served as a post-hoc indicator of which quality attributes contributed most to a given anomaly flag.

2.8. The Proposed ANN-Based Quality Control Framework

The findings from the three case studies were synthesised into a five-stage, multi-modal quality control framework designed to be adaptable across the diverse data environments of Nigerian manufacturing industries [22, 20]. Figure 1 summarises the end-to-end workflow used in the study, while Figure 2 presents the ANN architectures adopted for the three case studies.

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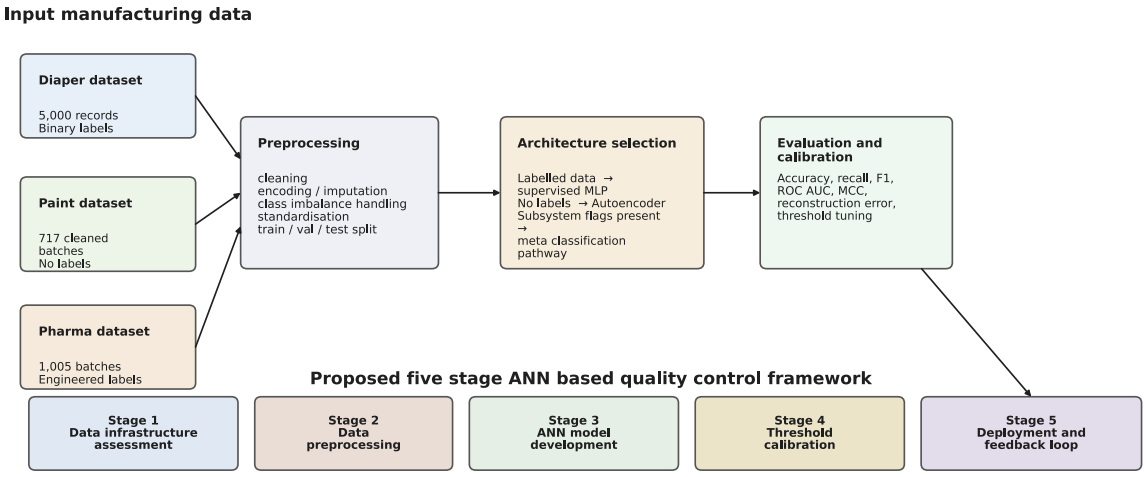

Figure 2. End-to-end study workflow and the proposed five-stage ANN-based quality control framework

Stage 1: Data Infrastructure Assessment: Manufacturers are categorised into three tiers based on data availability. Tier 1 (no QC labels) follows the unsupervised Autoencoder pathway. Tier 2 (binary labels, limited records) follows the supervised MLP pathway with class-weight balancing. Tier 3 (binary labels plus sub-system diagnostic outputs) follows the supervised MLP meta-classification pathway.
Stage 2: Data Preprocessing: All collected data undergoes removal of administrative identifiers, categorical encoding, missing value treatment, class imbalance handling through oversampling or class-weight balancing, and feature standardisation using StandardScaler fitted exclusively on training partitions.
Stage 3: ANN Model Development: The appropriate architecture is selected based on the data tier. Supervised models are trained with Adam, ReLU activations, L2 regularisation, and early stopping. Where computational resources permit, hyperparameter grid search is conducted [27].
Stage 4: Threshold Calibration and Evaluation: Decision thresholds for supervised models are tuned on validation data to optimise FAIL recall or FAIL F1-score in line with each sector's cost structure. For the Autoencoder, the anomaly threshold is set at the 99th percentile of the validation set reconstruction error. Final performance is reported on the held-out test set using the full metric suite [29].
Stage 5: Deployment and Feedback Loop: Deployed models are monitored for production drift over time. Periodic retraining is scheduled to accommodate changes in process distribution arising from equipment wear, supplier changes, or process modification. This ensures the framework supports continuous quality improvement rather than one-time deployment.

Table 3. Mapping of study objectives to methodology components and case study applications

Objective	Methodology Component	Case Study Application
Design and implement ANN models for defect identification	MLPClassifier (Scikit-learn); PyTorch Autoencoder; three tailored architectures	Diaper: Input(24/30)→128→64→32→Output; Paint: 8→16→8→3→8→16→8; Pharma: Input(38)→64→32→Output
Evaluate ANN performance on real-world data	Train/validation/test splits; accuracy, precision, recall, F1, ROC-AUC, MCC, AP, 5-fold CV	Held-out test sets across all three companies
Validate model reliability and robustness	Early stopping; L2 regularisation; stratified splits; threshold tuning; latent space visualization	Diaper Model B: 100% accuracy; Pharma CV ROC-AUC: 0.90 ± 0.028; Paint anomaly ratio: 13.73 times
Propose a practical ANN-QC framework	Five-stage multi-modal framework: assess → preprocess → develop → calibrate → deploy	Synthesised from findings across all three case studies

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Objective	Methodology Component	Case Study Application
Validate framework via case study implementation	Two modelling paradigms; three datasets with differing structures and sectors	Armstrong Paint, Moflix Diaper, Pharmaceutical Co.

3.0 Results and Discussion

3.1. Case Study I: Diaper Manufacturing

3.1.1. Exploratory Analysis

The diaper dataset comprised 5,000 production samples with 24 features spanning process parameters, material measurements, mechanical properties, and contextual variables. The dataset was complete with no missing values a characteristic typical of sensor-driven FMCG production systems. The class distribution was 86.2% PASS and 13.8% FAIL. The most frequent fault types were covering integrity failure (3.8%) and core placement error (3.1%), followed by seal failure (2.1%), SAP distribution issues (1.9%), tape adhesion defects (1.9%), and elastic cuff faults (1.8%). Machine M4 recorded the highest fail rate at 15.7%, while Machine M2 had the lowest at 12.2%, suggesting inter-machine variability likely linked to calibration or maintenance differences [31].

Critically, linear correlations between individual sensor features and the quality label were below 0.04 in magnitude. This finding indicates that defects arise from compound, multivariate threshold effects rather than deviations in any single sensor reading precisely the kind of non-linear relationship that ANNs are designed to capture [32]. The Night shift recorded the highest fail rate among operational variables, while the S diaper size showed a marginally elevated defect rate, possibly due to the greater manufacturing complexity of smaller variants.

3.1.2. Model Performance

Two MLP models were developed. Model A used 24 sensor-only inputs, simulating a realistic development scenario where only raw process data is available. Model B used 30 inputs, incorporating the six binary sub-system defect flags and functioning as a meta-classifier over existing alarm outputs. Both models shared the same architecture: Input(n) → Dense(128, ReLU) → Dense(64, ReLU) → Dense(32, ReLU) → Output(Sigmoid).

At the tuned threshold of 0.92, Model A achieved an overall accuracy of 75.6%, ROC-AUC of 0.5327, and FAIL recall of 21.4%. The near-diagonal ROC curve confirms that Model A performed with limited discriminative ability on raw sensor data alone. This result is consistent with the low feature-label correlations identified during exploration and with findings by Albers et al. [33], who showed that defect classification from raw process parameters alone typically requires richer datasets or more sophisticated feature engineering to achieve useful recall rates. Feature importance analysis identified waistband tension, core weight, ambient temperature, cover integrity score, and seal integrity score as the most influential inputs.

Model B, by contrast, achieved perfect performance on the held-out study sample: 100% accuracy, ROC-AUC of 1.000, and 100% FAIL recall, converging in just 22 epochs. This result should be interpreted carefully. The six additional binary signals supplied to Model B were not generic raw-sensor variables; they were structured sub-system defect indicators generated upstream by the production line itself. In other words, Model B was solving a signal-integration or meta-classification problem, not the harder task of inferring all defects from raw sensor data alone. Its perfect performance therefore demonstrates the value of combining distributed machine diagnostics within a single ANN layer, but it should not be read as evidence that perfect generalisation would automatically occur in other plants or over longer production periods without external validation [34].

Table 4. Performance comparison of Model A and Model B for the diaper manufacturing case study

Metric	Model A (Sensor Only)	Model B (Full Features)
Accuracy	75.6%	100.0%
ROC-AUC	0.5327	1.0000
FAIL Recall	21.4%	100.0%
FAIL F1-Score	0.1938	1.0000
Training Epochs	85	22
Input Features	24	30

The contrast between Model A and Model B delivers an important practical lesson: an ANN's diagnostic value is directly contingent on the informativeness of its input features. Where sub-system diagnostic outputs already exist, incorporating them as ANN inputs transforms a modest raw-sensor classifier into a high-performing meta-

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classifier. This supports the framework's recommendation to progressively integrate available data streams as manufacturing infrastructure matures.

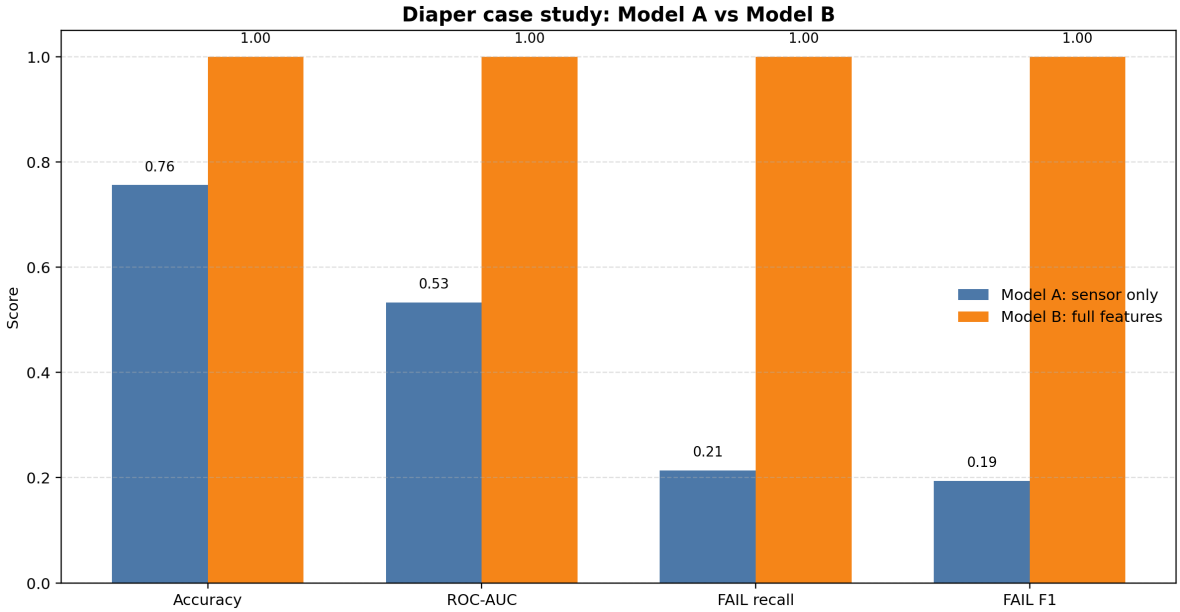

Figure 3. Comparative performance of diaper Model A (sensor only) and Model B (full features)

3.2. Case Study II: Paint Manufacturing

3.2.1. Dataset and Anomaly Detection Results

The paint dataset comprised 717 cleaned batch records covering eight physicochemical quality attributes: pH, specific gravity, fineness of grind, viscosity, drying time, temperature, spread rate, and colour code. A key challenge was the complete absence of historical PASS/FAIL labels a common situation in African manufacturing facilities where structured QC logging has not been systematically implemented [22]. An unsupervised Autoencoder was therefore selected, learning the statistical profile of normal production and flagging batches that deviate from this learned norm through elevated reconstruction error.

Training and validation MSE converged steadily from approximately 1.08 to 0.179 (training) and 0.251 (validation), with a train-validation gap of 0.072, indicating controlled, non-severe overfitting consistent with Autoencoder behaviour on small tabular datasets. The anomaly threshold was calibrated at the 99th percentile of the validation set reconstruction error distribution (threshold = 2.0048). Figure 4 presents both the Autoencoder training profile and the reconstruction-error separation achieved on the held-out test set.

Applied to the 108 held-out test batches, the Autoencoder identified one anomalous batch (0.9% of the test set), with a reconstruction error of 2.34 and 13.73 times the mean normal test batch error of 0.17. This separation demonstrates that the flagged batch's quality profile was sufficiently unusual that the model, trained on normal batches only, could not reconstruct it faithfully. Latent space projections further confirmed this finding: the 107 conforming test batches clustered within the training distribution, while the anomalous batch was visibly displaced across multiple dimensional projections a geometric separation corroborating the high reconstruction error.

Table 5. Autoencoder anomaly detection results for the paint-manufacturing case study

Metric	Value
Total test batches	108
Normal batches (on-spec)	107 (99.1%)
Anomalous batches (off-spec)	1 (0.9%)
Mean reconstruction error Normal	0.1704
Reconstruction error Anomalous batch	2.3406
Anomaly-to-normal RE ratio	13.73 times
Anomaly threshold (99th percentile)	2.0048
Final training loss (MSE)	0.1791
Final validation loss (MSE)	0.2512

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This result is practically meaningful. Conventional manual inspection focuses on individual attribute specifications in isolation, making it unlikely to detect batches that are only anomalous when multiple quality parameters are considered jointly [35]. The Autoencoder, operating on the full eight-dimensional feature profile simultaneously, naturally captures these multivariate deviations. The latent space separation also aligns with the digital twin paradigm proposed by Huang et al. [36], where learned representations of normal production serve as a virtual baseline for quality comparison.

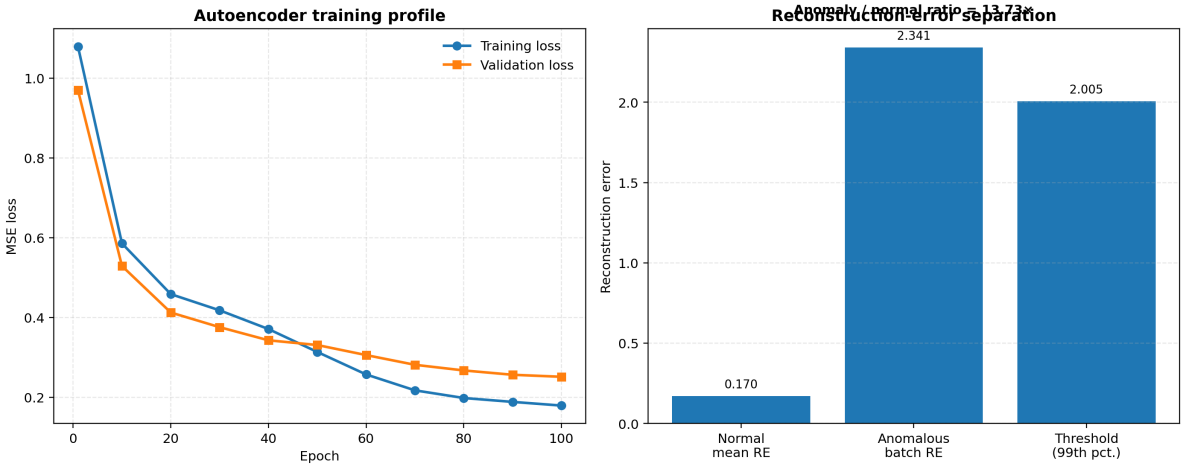

Figure 4. Paint Autoencoder training profile and reconstruction-error separation on the held-out test set

3.3. Case Study III: Pharmaceutical Manufacturing

3.3.1. Label Engineering and Class Distribution

The pharmaceutical dataset contained 1,005 batch records for a cholesterol-lowering film-coated tablet. No pre-constructed quality label was available, so a binary QC_PASS label was engineered from five final product attributes using internationally recognised regulatory standards, as shown in Table 2. A batch received QC_PASS = 1 only if all five criteria were simultaneously met; failure on any one criterion produced QC_PASS = 0. This approach is consistent with established practice in pharmaceutical quality informatics [24]. The resulting class distribution was 887 PASS (88.3%) and 118 FAIL (11.7%) an 8:1 imbalance typical of pharmaceutical manufacturing, where non-conformance represents the tail of the process capability distribution.

3.3.2. Model Performance

The baseline ANN achieved test set accuracy of 90.5%, ROC-AUC of 0.9082, and an MCC of 0.4946. However, FAIL recall stood at 46% meaning approximately 54% of non-conforming batches were missed at the default 0.5 threshold. While overall accuracy appeared strong, this level of FAIL recall is insufficient for pharmaceutical QC, where regulatory frameworks require near-complete interception of non-conforming product [24].

The tuned model improved accuracy to 92.5%, ROC-AUC to 0.9098, and MCC to 0.6049, an 11-percentage-point improvement in the most informative imbalanced classification metric [25]. FAIL recall improved to 54%, meaning that 13 of the 24 non-conforming test batches were correctly intercepted. However, 11 FAIL batches would still have been released if the model were used in isolation, while 4 conforming batches would have been incorrectly rejected. This pattern underscores both the promise and the residual risk of using ANN-based screening in a high-stakes pharmaceutical QC setting. Figure 5 summarises the comparative performance of the baseline and tuned pharmaceutical models.

Table 6. Performance comparison of baseline and tuned ANN models for the pharmaceutical case study

Metric	Baseline ANN (64-32-16)	Tuned ANN (64-32)
Accuracy	90.5%	92.5%
ROC-AUC	0.9082	0.9098
MCC	0.4946	0.6049
FAIL Precision	0.65	0.76
FAIL Recall	0.46	0.54
FAIL F1-Score	0.54	0.63

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Metric	Baseline ANN (64-32-16)	Tuned ANN (64-32)
False Negatives (missed defects)	13	11
False Positives (incorrect rejections)	13	4

Feature importance analysis via permutation importance identified film-coating average hardness and minimum tablet hardness as the two most influential predictors physically interpretable findings, since hardness directly governs dissolution behaviour. This aligns with pharmaceutical Process Analytical Technology (PAT) frameworks that identify the compression and coating stages as primary quality determinants [24].

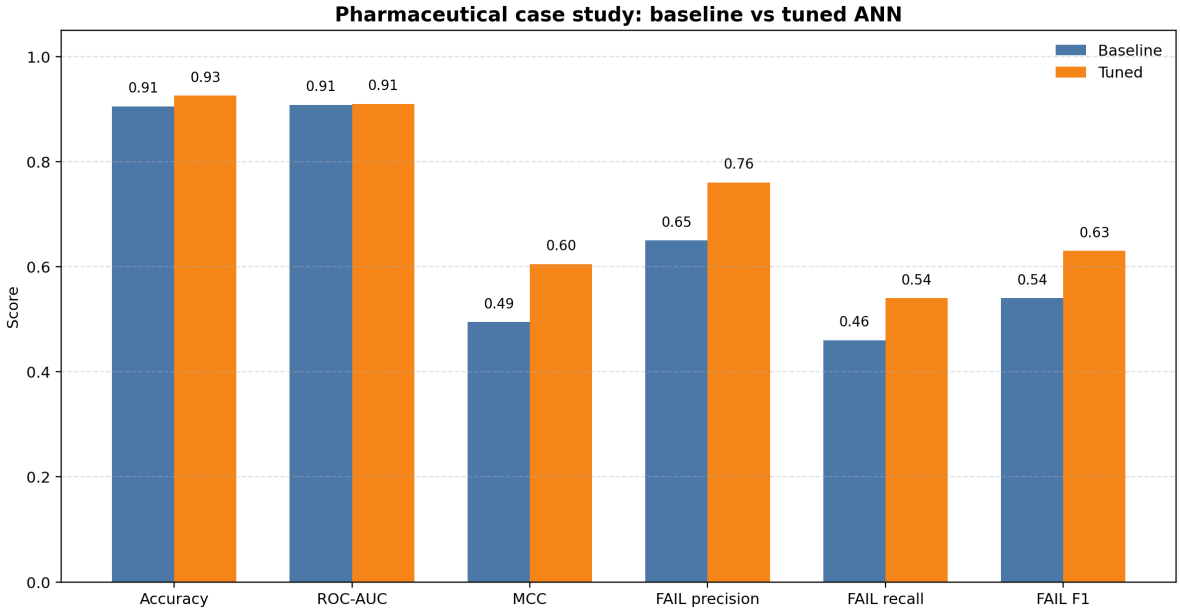

Figure 5. Comparative performance of the baseline and tuned pharmaceutical ANN models

The residual 46% missed defect rate in the tuned model reflects the limited number of FAIL training samples (n = 94). Future work should explore SMOTE for minority class augmentation, threshold reduction below 0.5, and ensemble methods combining ANN predictions with rule-based filters approaches shown to improve minority-class recall in similar pharmaceutical tasks [24].

The pharmaceutical ANN's ROC-AUC of 0.9098 is comparable to the 0.88–0.95 range reported by Nagy et al. [24] for ANN-based pharmaceutical batch classification, confirming that the model's performance is consistent with the best available evidence in this domain.

3.4. Cross-Case Synthesis and Framework Validation

3.4.1. Comparative Analysis

Table 7. Cross-case comparative summary of ANN modelling approaches and performance outcomes

Dimension	Diaper (Model A)	Diaper (Model B)	Paint	Pharmaceutical
Approach	Supervised MLP	Supervised MLP	Unsupervised Autoencoder	Supervised MLP
Dataset Size	5,000	5,000	717 batches	1,005 batches
Features	24	30	8	38
FAIL/Anomaly Rate	13.8%	13.8%	0.9% detected	11.7%
Best Accuracy	75.6%	100.0%	N/A	92.5%
Best ROC-AUC	0.5327	1.0000	N/A	0.9098

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Dimension	Diaper (Model A)	Diaper (Model B)	Paint	Pharmaceutical
Key Challenge	Low signal in raw sensors	None (perfect)	No labelled data	Small FAIL class (n=94)
Primary Technique	Oversampling + threshold tuning	Meta-classification	99th percentile threshold	Class weighting + grid search

A consistent finding across all three case studies is that ANN performance is directly modulated by feature informativeness. In the diaper case, performance jumped from a ROC-AUC of 0.53 on raw sensors alone to 1.00 when sub-system alarm signals were incorporated. In the pharmaceutical case, careful exclusion of label-derived features and inclusion of upstream in-process measurements were essential to constructing a genuinely predictive model. In the paint case, the complete absence of historical labels necessitated a different paradigm entirely. These findings reinforce the argument by Liu et al. [20] that data infrastructure investment is a fundamental precondition for effective AI-driven quality control.

3.4.2. Alignment with the Literature

The results align with and extend previous findings in several important respects. The pharmaceutical ANN's ROC-AUC of 0.9098 sits within the 0.88–0.95 range reported by Nagy et al. [24] for ANN-based pharmaceutical batch classification. The diaper Model B's perfect meta-classification mirrors findings by Tao et al. [34], who showed that structured diagnostic outputs used as ANN inputs can yield near-perfect quality classification. The limitations of raw-sensor-only classification in Model A are consistent with Kausik et al. [32], who found substantially lower FAIL recall when models rely solely on individual process variables. The paint Autoencoder's 13.73 times anomaly-to-normal reconstruction error ratio corroborates findings on Autoencoder effectiveness in assembly line anomaly detection, and the latent space separation aligns with the digital twin paradigm proposed by Huang et al. [36].

More broadly, the results support the now well-established position in the quality-control literature that ANN-based QC systems can outperform purely manual or rigid rule-based inspection workflows in defect detection, responsiveness, and adaptability when informative process data are available [17, 16, 10]. At the same time, the present study also shows that performance depends strongly on data quality, label structure, and feature informativeness. The contribution of this work is therefore not to claim unconditional ANN superiority in every manufacturing setting, but to show, using Nigerian case studies, the specific conditions under which ANN-based QC becomes practically useful.

3.4.3. Practical Implications for Nigerian Manufacturing

Three practical implications emerge clearly from these findings. First, ANN-based QC does not require large, perfectly labelled datasets or specialised hardware. The paint Autoencoder was trained on 717 records with eight features in a standard GPU environment within 100 epochs well within the reach of medium-scale manufacturers. The diaper and pharmaceutical ANNs were built with freely available Python libraries and trained within minutes, consistent with Nagy et al. [24] characterisation of accessible ANN deployment infrastructure.

Second, the pathway to effective ANN-based QC need not be linear. Manufacturers without structured QC logging should begin with unsupervised anomaly detection, which requires only normal-batch data to establish a quality baseline. As records accumulate, they can progressively migrate to supervised classification the staged deployment philosophy embedded in the five-stage framework proposed in this study.

Third, the pharmaceutical case demonstrates that ANNs can successfully predict batch quality from upstream process variables before final laboratory testing is completed, enabling a shift from reactive to predictive quality assurance [37]. This has direct relevance for reducing inspection burden and batch rejection rates in Nigerian pharmaceutical manufacturing.

3.4.4. Framework Validation

The case study results collectively fulfil all five study objectives. Objective 1 was demonstrated across all three contexts through the design and implementation of three distinct ANN architectures on real Nigerian manufacturing data. Objective 2 was met through rigorous train-validation-test protocols, cross-validation, and multiple evaluation metrics. Objective 3 was supported by Model B's perfect test set performance, the pharmaceutical ANN's consistent five-fold cross-validation ROC-AUC of 0.9001 ± 0.028, and the Autoencoder's clear separation between normal and anomalous batches. Objective 4 is substantiated by the multi-modal framework, which accommodates supervised classification for labelled environments, unsupervised anomaly

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detection for unlabelled contexts, and meta-classification for facilities with sub-system diagnostic infrastructure. Objective 5 is directly fulfilled by the three case studies, each representing a distinct sector and data regime within Nigerian manufacturing.

Overall, the results confirm that ANN-based quality control frameworks, when appropriately adapted to each manufacturing context's data availability and operational realities, offer a viable and practically significant improvement over conventional quality control methods for Nigerian manufacturing industries [22].

4.0 Conclusion

This study set out to develop and validate an ANN-based quality control framework for Nigerian manufacturing industries a context where persistent defect problems, reactive inspection practices, and limited data infrastructure have long constrained manufacturing performance. The results demonstrate that Artificial Neural Networks are technically viable, practically implementable, and contextually appropriate for quality control across diverse Nigerian manufacturing environments.

Three key empirical results anchor this conclusion. The pharmaceutical ANN achieved a ROC-AUC of 0.9098 and 92.5% accuracy on a real, class-imbalanced dataset, with five-fold cross-validation confirming stability at 0.9001 ± 0.028. The diaper meta-classification model achieved perfect held-out sample performance, 100% accuracy and 100% FAIL recall, when sub-system diagnostic signals were incorporated as inputs. The paint Autoencoder identified a statistically anomalous batch with a reconstruction error nearly fourteen times the normal mean, entirely without labelled training data. Taken together, these results provide strong evidence that ANN-based quality control can deliver operationally meaningful benefits in Nigerian manufacturing, while also showing that the strongest performance emerges when model design is aligned with the information structure of the available data.

The study makes contributions across three dimensions. Theoretically, it develops a multi-modal quality control framework that integrates supervised and unsupervised neural network paradigms within a single coherent structure, guided by data infrastructure maturity. Unlike prior studies that examined supervised ANN classifiers or unsupervised autoencoders in isolation, this framework addresses the pathway problem providing a principled rationale for how manufacturers should begin their journey toward ANN-based QC, not just what the destination looks like [20]. Empirically, the study provides one of the few published instances of ANN-based quality control implemented on real manufacturing data from Nigerian industrial companies. Diaper FMCG, paint manufacturing, and pharmaceutical production are sectors substantially underrepresented in the global ANN-for-QC literature, which is dominated by automotive, electronics, and semiconductor applications [16, 39, 40]. Methodologically, the study demonstrates the practical value of a comprehensive multi-metric evaluation protocol including ROC-AUC, MCC, FAIL recall, precision-recall curves, and latent space visualisation for assessing ANN models under class-imbalanced conditions.

Equally important are the study's diagnostic insights. The near-random performance of the sensor-only diaper model is not a failure of the ANN methodology it is a precise indicator that the binding constraint lies in data infrastructure, not modelling capability. The 54% FAIL recall of the pharmaceutical model points specifically to the need for synthetic data augmentation and threshold adjustment as near-term improvement levers. These context-specific findings, enabled by rigorous multi-metric evaluation, are of the greatest practical value to manufacturers and practitioners seeking to understand not just whether ANNs work, but how and under what conditions they work best.

Several limitations must be acknowledged. The datasets were relatively modest in size, particularly the paint dataset (717 records) and the pharmaceutical FAIL class (118 instances), which constrained minority-class learning. The perfect study-sample performance of the diaper meta-classifier should also be interpreted cautiously, because it depended on highly informative sub-system defect flags and has not yet been externally validated on temporally separated production runs or additional facilities. The study did not benchmark the ANN models against alternative classifiers such as Random Forests, XGBoost, Support Vector Machines, or simpler linear baselines on the same datasets; accordingly, the contribution of this work is to establish ANN feasibility in three Nigerian manufacturing settings rather than to assert universal algorithmic superiority [32, 39, 41, 42]. The Autoencoder for paint manufacturing operates without ground-truth labels, so the real-world false positive rate cannot be formally estimated. In addition, all models were trained and evaluated on historical datasets, and production drift was not empirically tracked over time.

For future research, four directions are particularly important. First, the ANN pipelines developed here should be benchmarked directly against tree-based, kernel-based, and linear classifiers on the same datasets, since recent reviews show that manufacturing QC performance is task-dependent and that comparative evaluation remains essential [32, 39, 41]. Second, explainable AI techniques such as SHAP and LIME should be incorporated to provide batch-level explanations of individual quality predictions, which is especially critical in the pharmaceutical context where quality decisions must be auditable under ICH Q10 and GMP frameworks [24]. Third, external validation on temporally separated batches, additional factories, and prospective pilot deployments should be

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undertaken to test robustness under distribution shift. Fourth, future work should extend to RNNs and LSTM networks for time-series quality prediction from sequential sensor data, and to CNNs for optical surface inspection, particularly relevant to paint surface quality assessment where shade consistency and coverage require visual analysis [42, 43].

For practitioners, the central message is straightforward. Structured data logging is a foundational investment, regardless of whether ANN deployment is an immediate goal. Companies without existing quality labels should adopt the Autoencoder pathway as an accessible entry point into AI-assisted monitoring, requiring only records of normal production and open-source tools. Those with existing sub-system diagnostic outputs should prioritise integrating those signals as ANN inputs the performance difference between raw-sensor-only classification and meta-classification in this study was categorical. For policymakers, NAFDAC, the Standards Organisation of Nigeria (SON), and the Manufacturers Association of Nigeria (MAN) should develop sector-specific guidelines for the validation and regulatory acceptance of AI-based quality control systems, drawing on international precedents from the European Medicines Agency, the US FDA, and the International Council for Harmonisation (ICH).

The broader significance of this study lies in demonstrating that the path from current Nigerian manufacturing practice to intelligent, data-driven quality control does not require large capital investment in proprietary software or specialised hardware. It requires structured data, open-source tools, and the organisational commitment to treat quality as a continuously improving, data-driven practice [21]. This study has shown that path and provided a framework for walking it.

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