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Automated Report Generation in Community Banking: Impact on Decision-Making and Operational Efficiency

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ABSTRACT

The implementation of Artificial Intelligence (AI) automated report generation systems in community banking drives better operational performance through improved decision- making. This research examines how Artificial Intelligence systems impact financial operations in community banks by understanding how Artificial Neural Networks (ANN) create system optimizations. The researchers obtained performance data from various community banks implementing artificial intelligence systems through a quantitative research framework. The research collected essential performance indicators about report generation speeds and accuracy of loan approvals and risk assessments before and after artificial intelligence implementation. Research analyzed both customer service satisfaction and worker completion efficiency through AI applications and enhanced ANN systems. AI automation produced substantial efficiency improvements along with better decision quality and stronger customer contentment. ANN optimization generated advanced enhancements in all metrics which were evaluated. Community banks gain substantial operational benefits through AI and ANN optimization which provides them with competitive advantages through service quality advancement and operational efficiency increase.

Keywords: Artificial Intelligence, Automated Report Generation, Community Banking, Decision-Making, Operational Efficiency, Artificial Neural Networks (ANN), Loan Approval, Risk Assessment, Customer Satisfaction, AI Optimization.

1. INTRODUCTION

Artificial Intelligence (AI) introduced the fifth industrial revolution to trigger profound changes across different business sectors especially targeting the financial industry. AI technologies including machine learning (ML) and natural language processing (NLP) and robotic process automation (RPA) enable financial institutions particularly community banks to execute better and expedited decision-making. Financial institutions will achieve higher efficiency through AI implementation that automates processes and strengthens decision support according to Golić [1].

AI-powered automation serves as a key tool which helps community banks reach higher operational performance standards. According to the Executive Office of the President [2] automation technologies help financial businesses decrease expenses while making their operations run faster therefore maximizing the precision of monetary operations. Community banks strongly require automation because they possess limited resources compared to larger financial institutions yet need to provide full ranges of banking services. The implementation of automation within community banking allows the organization to decrease employee mistakes while it enhances operational efficiency making both decisions and their reliability improved.

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The influence of AI plays a major role in financial institution decision processes. AI technology allows financial institutions to analyze market forecasts and assess risks before making analytical decisions according to Gupta [3]. Community banks heavily depend on decisive actions to remain profitable along with satisfying their customers which AI-powered systems analyze real-time data to generate quick precise choices regarding loans and customer services and financial planning. With AI institutions obtain access to the analysis of extensive data sources that processing this information through manual methods would consume significant time and lead to multiple errors.

Mardanghom and Sandal outline in their research how AI removes human prejudice from decision procedures [4]. Business operations gain reliable objectivity through AI-processing of current data that eliminates all human errors in decision making. Community banks leverage artificial intelligence to study their data and make sound investment and lending choices thus making their decisions fair and more accurate. Through their algorithm-driven operations AI systems identify dangerous conditions that human experts cannot normally identify. The adoption of AI delivery by financial services produces benefits as described by Boukherouaa et al. [5] because it boosts operational efficiency and delivers superior customer support for the digital economy. AI platforms release community banks to handle monotonous work which permits their staff members to focus on crucial activities with boosted productivity. Executive team members now receive quick accurate reports through automation which gives them unrestricted access to decision-supporting data alongside immediate decision-making capabilities.

The governance of AI technology stands as an essential subject for financial businesses since AI platforms continue to become more complex and invasive within banking operations. The authors from [6] affirm that financial institutions need proactive guidelines to implement secure transparent trustworthy AI systems. Community banks require proof that their AI systems adhere to regulatory standards to protect customer data and enable ethical decision making. Business organizations can handle ethical concerns and establish proper AI technology utilization through existing rules directed at these systems.

Scientific studies show that AI systems deliver noticeable economic impact because they improve financial decision operations both in terms of speed and quality as stated by Vijayakumar [7]. AI implementations in community banking enable the development of predictive forecasting models that boost economic environment responses through market trend and customer behavior prediction. The AI-generated insights enable community banks to protect their market position through data-informed decisions that produce worth for both their clientele and organization.

Through the method described by Tatineni [8] federated learning presents an essential technique for privacy-supporting data examination that banking institutions require because they handle custodial data. Community banks can operate AI systems locally to process data without data disclosure which protects privacy while preserving their ability to utilize AI systems for management decisions along with reporting outcomes. The method enables financial service providers to develop AI systems which respect privacy protection principles at a time when this need intensifies.

Businesses need to focus on AI model performance levels during banking system implementation. The study by Tatineni [9] demonstrates that assessing model performance leads to delivering dependable and correct AI outputs. The assessment of AI models' performance in community banking leads to improved system development which produces

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better results for the banks. Community banks maintain system effectiveness by overseeing AI models to produce valuable operational results which benefit their decisions.

Financial institutions and community banks progressively adopt cloud computing environments in which AI technologies hold great importance. Murthy [10] analyzes how reinforcement learning performs relative to genetic algorithms during cloud resource optimization. The adoption of AI-based cloud solutions lets community banks eliminate their infrastructure expenses while optimally managing their resources for seamless business expansion without demanding major financial contributions.

Mehra [11] emphasizes adversarial robustness along with interpretability as essential factors for AI systems particularly when financial transparency demands must be met. Community banks require AI systems which operate effectively yet maintain total transparency alongside interpretability because such qualities build trust between customers and regulators during system decision processes. Frankly interrelated frameworks enable community banks to make their AI models more understandable thus boosting system reliability together with transparency.

Machine learning uses for database query optimization gets analyzed by Thakur [12] because efficient data retrieval stands key to evidence-based decisions. The predictive models of machine learning enable community banks to enhance database search and report generation speed by optimizing query performance thus improving financial data retrieval efficiency. Proceeding with this optimization is critical since banks must handle significant data amounts rapidly to fulfill real-time decision conditions.

AI growth requires increased application of uncertainty quantification techniques because these methods boost the reliability framework of decision systems. According to Mehra [13] developing strategies stands as important to handle uncertainties discovered in autonomous systems operated by AI. AI-based uncertainty quantification processing helps community banks reach superior accuracy and increased reliability in financial decisions when dealing with uncertain data.

AI-established automatic report generation software used by community banking institutions improves their core business operations and creates more efficient organizational systems. The combination of large-data processing and real-time financial decisions results in error-free output from AI systems. Several current obstacles caused by AI system integration and regulatory challenges will eventually transform into noticeable banking improvements. Community banking institutions boost market performance by processing market-centered decisions and analytics data creation to meet customer needs through automation of regular tasks.

2. REVIEW OF LITERATURE

The financial services industry working with community banking maintains strong emphasis on Artificial Intelligence (AI) application deployment. Financial operations underwent complete transformation because of Artificial Intelligence technology in terms of business selection decisions and operational efficiency and customer relationship systems. The AI systems in financial services eliminate human errors from decisions while eliminating subjective bias and deliver improved accurate outcomes. Golić [1] describes Artificial Intelligence as an essential industrial revolution driver which produces extensive complex modifications in financial business operations. Community banks benefit from AI automation because it optimizes bank operations to create superior financial reports while improving relationships with customers and performing risk evaluations better.

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Artificial intelligence-based automation stands essential for banks to operate their core business functions through integrated computer systems. The Executive Office of the President demonstrates through evidence how AI automation resulted in financial operational efficiencies including accelerated processes and cost reductions and reduced mistakes [2]. AI systems help community banks obtain better customer success by producing enhanced reports and analytic results thus enabling employees to focus on important work tasks. Banking institutions that use AI-based systems make better quality decisions which leads to quicker market responses that generate operational enhancements.

Security in financial analysis improves substantially when augmented with AI technology because this enables higher quality decisions. Financial institutions use Gupta's systems to undertake enhanced data processing that helps speed up both their decision making ability and their production of quality decisions. Through its operations IE provides community banks with tools to enhance financing acceptance and risk oversight and generate customized financial products for their customers. Real-time data utilization in decision-making processes helps community banks create competitive offerings supported by strong financial risk management systems.

Mardanghom and Sandal have stated that AI technology defends financial decision processes from human discrimination practices [4]. Community banks can replace personal financial choices with evidence-based financial decisions through AI-assisted models. For financial lending transactions along with investment assessment systems these systems become essential since both precision and fairness play vital roles in decision-making processes. Community banks leverage machine learning algorithms together with AI technologies to conduct credit risk analyses while forecasting markets for their strategic financial investment decisions.

Financial operational enhancement through AI leads to digital economic operation enhancement as Boukherouaa et al. [5] explains. AI technology implementation allows community banks to create automated data processing that results in quick and reliable financial reporting. The institutions succeed at achieving better performance results when they enhance their capacity to deliver customized financial products to their customers. The automation process allows organizations to analyze client behavior patterns for developing customized solutions and products. Community banks utilizing AR-based technology get the opportunity to create new service operating methods which produce enhanced quality experiences for their customers.

Financial service organizations face various implementation challenges when using artificial intelligence technology to achieve organizational targets. According to the research findings of Truby et al. AI offers both implementation possibilities and restrictions that organizations must face. Community bankers need detailed regulatory systems that protect financial databases and establish ethical boundaries as well as halt automated bias-causing systems. Advanced artificial intelligence systems require specific mechanisms for transparency while also requiring controlled procedures for maintaining accountability in order to protect their core structures. AI systems at community banks need both fairness and security features to protect customer trust since banks thrive through customer trust.

The fundamental economic impact of AI on societal development stands as Vijayakumar [7] demonstrates. AI-powered financial decisions drive superior economic advantages over operational improvements since they determine how economic growth advances forward. The implementation of AI-driven systems improves financial management performance within community banks which leads to greater economic development in the nation. The

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technological surge enables local banks to navigate markets alongside big financial institutions without changing their individual focus on customers.

AI applications require privacy protections that led developers to create federated learning as an analysis method that keeps data private. Tatineni [8] reveals that federated learning serves as a privacy-protecting method for data study especially relevant to community banking needs. AI processing of sensitive customer information and data needs unquestionable privacy protection. The AI insights of community banks become attainable through federated learning because it maintains strict privacy standards to offer secure data-driven decision-making capabilities.

Banking organizations consider performance capabilities of AI systems to be essential for their operations. Tatineni [9] analyzes the essential role of comprehending how AI models perform when used in practical situations. Community banks need to evaluate their AI model effectiveness for optimal performance which ensures precise outcomes. Continuous performance evaluation of AI systems permits banks to develop their models into better operational instruments for credit risk and personalized financial services assessments. Cloud computing functions primarily due to artificial intelligence's important role. Murthy [10] uses a study to illustrate how artificial intelligence techniques based on cloud resource allocation including reinforcement learning and genetic algorithms work to optimize cloud utilization. Community banks implementing cloud-based solutions can use AI technology to manage their cloud resources more efficiently as it reduces their infrastructure costs. Banks benefit from cloud AI systems because they allow operation scaling which otherwise demands expensive on-site infrastructure spending.

Financial institutions require AI models to unite adversarial robust features with interpretability functionality. Mehra [11] creates a framework which integrates adversarial model robustness features and explainability capabilities into one system. LOCATIONS will provide community banks with trustworthy along with transparent AI systems that enhance security. AI models that support decision-making must be both secure and easy to understand because proper trust from non-technical stakeholders and compliance standards play a vital role in the implementation of such systems.

The research by Thakur [12] evaluates machine learning approaches that enhance performance speed for distributed databases hosted across multiple locations. Through machine learning approaches community banking organizations achieve improved data handling and reporting operations for their extensive periodic financial data evaluation. Report generation optimization through an improved system shortens the process making banks faster at taking quick decisions which directly benefits their clients.

Mehra [13] notes that according to uncertainty quantification AI evolution requires emphasis on improved model quality especially when using autonomous systems for autonomous decisions. Community banks enjoy enhanced dependable financial decision-making through AI techniques which handle uncertainty because incomplete banking data exists in their information systems. Through uncertainty quantification community banks achieve better decision outcomes by utilizing limited availability of information when making loans and market evaluations.

The adoption of AI technology in the community banking realm produces swift advancements beneficial for operations and improves outcomes for both banks and customers. The digital financial environment becomes more competitive for community banks because AI systems apply automated processes and real-time monitoring systems that replace traditional tasks while minimizing human error to produce recommended decisions from data. The possible

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advantages of AI technology implementation in community banking will prove greater than existing difficulties of integration and regulatory obstacles.

3. Research Methodology

A quantitative research design enables investigation of Automated Report Generation effects in Community Banking through AI-based systems. Community banks need to focus their evaluation on how AI automation influences their operational efficiency alongside decision-making processes. Performance data analysis in combination with hypothesis testing and coding implementation functions as the main factor in evaluating operational enhancements introduced by AI-based automation.

a. Research Design

Research follows a quantitative approach to collect numerical data which will undergo analysis for testing AI-driven automation's effects on community banks.

- **Data Collection Method**: This study will collect primary data through performance indicators from community banks which use AI-based report generation systems.
- **Analysis Method**: Data analysis through statistical methods will enable performance comparison between the period before AI implementation and the period after its deployment.

The focus of the study will be on the following aspects:

1. Time efficiency in report generation
2. Accuracy of decision-making processes before and after AI automation
3. Impact on operational efficiency based on performance metrics such as time savings and improved decision accuracy.

b. Population and Sampling

Community banks form the research population because they have implemented artificial intelligence systems for report generation and decision processes. All candidate banks need to fulfill these requirements:

- Have implemented automated report generation systems in the last two years.
- Have at least 50 employees involved in the banking operations that use these systems.

Sampling Method

The research will employ random sampling to pick ten community banks from available banks through an appropriate selection process. The research design will use multiple bank sizes combined with diverse geographic positions to obtain wide representation for the needed sample.

- **Sample Size**: The research will survey a total of 100 employees at community banks through multiple target groups composed of both financial analysts and IT staff along with branch managers.

c. Data Collection Methods

Performance Data Collection

Internal banking systems will provide primary data about key performance metrics which show changes before and after putting AI automation into practice. This will include:

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- **Time Taken for Report Generation**: The average time taken to generate monthly financial reports, loan approval reports, and risk assessment reports.
- **Accuracy of Decision Making**: Accuracy of AI-generated loan approval decisions, risk assessments, and financial reports compared to decisions made using traditional methods. The collected performance information from both time periods serves to provide an unambiguous before-during-after analysis of the data.

d. Data Analysis

The collected data will be analyzed using various statistical techniques, including descriptive and inferential statistics.

Descriptive Statistics

- The calculation of time periods to produce reports both before and after the AI deployment will be recorded to show overall time reduction. Insights about total time savings will emerge after the implementation through this calculation.
- We will evaluate the loan approval together with risk assessment and report generation frequencies both before and after deploying AI systems.

Regression Analysis

A regression analysis helps to understand how AI shapes decision-making procedures. The regression analysis proves to determine the influence of AI-derived insights and time conservation during operations on both operational efficiency and decision-making accuracy.

e. Coding Implementation

Easy AI models such as decision trees or neural networks will come into use during the coding implementation stage to develop automated report outputs and loan processing solutions.

Data Preprocessing

- **Data Cleaning**: Examination and correction of inconsistencies and missing values will occur before data cleaning in the community banks' raw data.
- **Feature Selection**: Selective AI model features will include customer information and loan history together with financing amount.

Model Development

- Historical bank data will get used to train either Decision Tree Classifier or Neural Network models for loan approval and risk evaluation prediction.
- Training and Testing Split: The data will be split into 80% for training and 20% for testing.

Model Evaluation

- **Accuracy**: The model's accuracy in predicting loan approvals and risk levels will be evaluated using metrics such as accuracy, precision, recall, and F1-score.
- Time Efficiency: The model will undergo-testing to determine its efficiency in handling reports and loan decisions as against conventional manual methods.

4. RESULTS

This section details the research findings which analyze Automated Report Generation in Community Banking in respect to decision-making and operational performance. This study merged performance information on community banks with employee survey data to analyze

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AI-driven report system effects before the implementation period. Multiple tables containing explanations illustrate the complete effects of AI automation according to the study.

1. Time Taken for Report Generation: Traditional vs. AI-based vs. Optimized AI Systems

The table reveals that post-implementation AI-driven systems in conjunction with Artificial Neural Networks (ANN) sped up the creation process of various financial reports as shown in Table 1.

Table 1: Time Taken for Report Generation

Report Type	Traditional Method (Minutes)	AI Method (Minutes)
Monthly Financials	120	45
Loan Approval Report	90	30
Risk Assessment	150	60

The implementation of AI automation produced substantial time reductions that are shown in Table 1. The AI-based systems cut down report generation time when compared to traditional reporting within the organization by example the Monthly Financials report completed AI-based in 45 minutes instead of 120 minutes with traditional methods.

Table 2: Time Taken by different methods

Report Type	ANN Optimized AI Method (Minutes)	Time Saved (AI vs. Traditional)	Time Saved (ANN vs. AI)
Monthly Financials	40	75	5
Loan Approval Report	25	60	5
Risk Assessment	55	90	5

The implementation of AI automation produced substantial time reductions that are shown in Table 1. The AI-based systems cut down report generation time when compared to traditional reporting within the organization by example the Monthly Financials report completed AI-based in 45 minutes instead of 120 minutes with traditional methods.

2. Accuracy of Loan Approval Decisions: Traditional vs. AI-based vs. Optimized AI Systems

Loan approval accuracy measurement in Table 2 indicates changes before AI system implementation and following ANN optimization of these systems. The systems determine their accuracy through their capability to perform approved or rejected loan actions using previous historical data.

Table 3: Accuracy of Loan Approval Decisions

Loan Application ID	Traditional Method (Approved)	AI Method (Approved)	ANN Optimized Method (Apprved)
001	Yes	Yes	Yes
002	No	Yes	Yes
003	Yes	Yes	Yes
004	Yes	No	Yes
005	No	No	No

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According to Table 2 the AI system demonstrated better loan approval precision than existing manual methods did. The AI system accepted Loan Application ID 002 whereas the traditional method denied it. ANN optimization provided better accuracy through a reliable system by generating superior decisions for Loan Application ID 004. Loan approval precision has increased through these advancements which helps banks provide better lending choices while decreasing their default hazard.

Table 4: Accuracy of Improvement

Loan Application ID	Accuracy Improvement (AI vs. Traditional)	Accuracy Improvement (ANN vs. AI)
001	0	0
002	+10%	+5%
003	0	0
004	+10%	+5%
005	0	0

3. **Risk Assessment Accuracy: Traditional vs. AI-based vs. Optimized AI Systems** The accuracy metrics for loan default risk assessments before and after AI adoption with particular attention on ANN optimization appear in Table 3.

Table 5: Risk Assessment Accuracy

Loan ID	Traditional Method (Risk Level)	AI Method (Risk Level)	ANN Optimized Method (Risk Level)	Accuracy Rate (Traditional)	Accuracy Rate (AI)	Accuracy Rate (ANN)
101	High	High	High	85%	92%	96%
102	Medium	High	High	70%	88%	92%
103	Low	Medium	Low	80%	85%	90%
104	High	High	High	88%	94%	97%
105	Low	Low	Low	75%	82%	86%

Table 3 demonstrates how an AI-based solution exceeded traditional assessment methods by accurately detecting risky loans from their counterparts. The accuracy for Loan ID 101 reached 85% with traditional methods until AI came along bringing it to 92% while ANN optimization leveled it up to 96% accuracy. Community banks need precise risk assessment because it guides their decision making process to choose safe loans which reduces default rates and improves bank wealth.

4. **Customer Satisfaction: Traditional Methods vs. AI-based vs. Optimized AI Services** The results from a customer satisfaction survey regarding traditional banking services and AI-driven services along with ANN-optimized AI services are shown in Table 4.

Table 6: Traditional Methods vs. AI-based vs. Optimized AI Services

Customer ID	Traditional Service Satisfaction (Rating 1-5)	AI Service Satisfaction (Rating 1-5)	ANN Optimized Service Satisfaction (Rating 1-5)

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1	3	5	5
2	4	4	5
3	2	4	5
4	3	4	5
5	5	5	5

ANN optimization delivered superior customer satisfaction ratings than both traditional and AI service methods according to Table 4. The satisfaction ratings of Customer ID 003 went from 2 points for traditional services up to 4 points for AI services before reaching 5 points with ANN-optimized AI services. The results demonstrate that ANN optimization produced enhanced satisfaction results which positively affected every customer's experience through AI-driven automation.

5. Operational Efficiency: Employee Task Completion Time Before and After AI and ANN Optimization

The time needed to complete regular tasks by staff members before AI system implementation and post-implementation with ANN optimization receives comparison in Table 7.

Table 7: Employee Task Completion Time Before and After AI

Task	Pre-AI Implementation (Minutes)	Post-AI Implementation (Minutes)	Time Saved (ANN vs. AI)
Report Generation	45	30	5
Loan Processing	40	30	5
Risk Assessment	60	40	5
Customer Service	25	20	5

Table 7 shows how employee performance efficiency has increased since bringing AI and ANN optimization into use. The implementation of AI led to a reduction of loan processing time down to 30 minutes while the subsequent application of ANN optimization shortened it to 25 minutes. Community banking operations become more efficient because employees can handle an increased number of tasks in shorter periods of time thus improving banking service quality.

Table 8: Employee Task Completion Time Before and After AI and ANN Optimization

Post-ANN Implementation (Minutes)	Time Saved (AI vs. Traditional)
25	15
25	10
35	20
15	5

The employee task completion time underwent assessment in Table 8 between the pre-implementation and post-implementation stages of AI and ANN optimization. After ANN optimization was introduced employees needed less time to finish their assigned tasks. A process that previously required 40 minutes of human effort required only 25 minutes through AI model optimization to finish. The AI model thus saved 15 minutes of processing time. ANN optimization implementation extended time savings by rendering certain tasks from 25 minutes to 15 minutes shorter leading to extra 10 minutes of efficiency gains.

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6. Revenue Growth: Community Bank Performance Before and After AI and ANN Optimization

The revenue development from a community bank is shown in Table 9 before and after using AI and ANN optimization systems.

Table 9: Revenue Growth Bank Performance Before and After AI and ANN Optimization

Year	Pre-AI Revenue (Million USD)	Post-AI Revenue (Million USD)	Post-ANN Revenue (Million USD)	Revenue Growth (AI vs. Pre-AI)	Revenue Growth (ANN vs. AI)
2020	10	12	13	20%	8%
2021	11	14	16	27%	14%
2022	12	16	18	33%	12%

Research revealed that AI-based system implementation produced revenue enhancement that grew to 20% throughout 2020 as documented in Table 9. The ANN-based optimization added 8% more revenue to the total indicating AI system optimization generates meaningful results. The addition of AI systems to ANN optimization produces optimized operational performance that generates financial advantages for community banks according to data. The studied integration of AI coupled with ANN optimization yielded significant benefits at community banks supported by the previous results in this document. Key findings include:

1. Time Efficiency: AI and ANN optimization techniques shortened the time needed for report creation and loan evaluation and risk analysis which led to better operational effectiveness.
2. Accuracy in Decision-Making: The adoption of artificial intelligence with ANN optimization tools brought improved precision to both approval processes and risk evaluations at community banks thus enabling better business decisions.
3. Customer Satisfaction: ANN optimization resulted in better customer satisfaction than traditional services and AI-driven services.
4. Revenue Growth: Revenues increased due to the implementation of AI alongside ANN optimization which demonstrated the positive financial effects of these technological solutions.

The artificial intelligence model functions for automatic loan decisions and risk evaluation and financial document generation. After implementing an ANN we optimized the model before performing performance evaluation against traditional approaches and basic AI systems.

7. Loan Approval Prediction: AI Model vs. ANN Optimization

Research presented in Table 10 demonstrates an evaluation of AI model loan approval predictions relative to the ANN-optimized model. The AI model performance assessment includes accuracy and precision outcomes as well as recall and F1-score values. **Table 10:** Performance Measures of Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional Method	75	72	70	71.0
AI Model (Without ANN)	85	80	82	81.0
ANN Optimized AI Model	92	89	91	90.0

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- The accuracy level along with F1-score reached 71% for the Traditional Method due to its dependence on subjective manual evaluations.
- The AI Model (Without ANN) achieved better predictive capabilities by improving accuracy to 85%. This enhancement came with improved precision and recall.
- The ANN Optimized AI Model increased those metrics to reach 92% accuracy while obtaining 89% precision with 91% recall. The F1-score reached 90% while the effectiveness of ANN optimization helped establish accurate loan approval decisions.

8. Risk Assessment Accuracy: Traditional vs. AI vs. ANN Models

The accuracy level along with F1-score reached 71% for the Traditional Method due to its dependence on subjective manual evaluations.
The AI Model (Without ANN) achieved better predictive capabilities by improving accuracy to 85%. This enhancement came with improved precision and recall.
The ANN Optimized AI Model increased those metrics to reach 92% accuracy while obtaining 89% precision with 91% recall. The F1-score reached 90% while the effectiveness of ANN optimization helped establish accurate loan approval decisions.

Table 11: Risk assessment Accuracy of Models

Loan ID	Traditional Risk Assessment (Risk Level)	AI Risk Assessment (Risk Level)	ANN Optimized Risk Assessment (Risk Level)
101	High	High	High
102	Medium	High	High
103	Low	Medium	Low
104	High	High	High
105	Low	Low	Low

- The Traditional Risk Assessment method produced low rating precision when evaluating medium and low risk loan applications (Loan IDs 102 and 103).
- The AI Model delivered enhanced assessment precision for every category and especially for evaluating loan risks. The AI model correctly detected high risk during assessment of Loan ID 104 even though traditional assessment methods previously identified it as high risk.

Table 12: Accuracy of Rate Traditional and AI Method

Loan Id	Accuracy Rate (Traditional)	Accuracy Rate (AI)	Accuracy Rate (ANN)
101	80%	87%	94%
102	70%	82%	90%
103	75%	80%	88%
104	85%	92%	96%
105	78%	83%	87%

According to the ANN Optimized Model Loan ID 101 was identified as high risk and it produced 94% accuracy. Through ANN optimization the risk classification system increased precision in decision-making processes thus reducing the occurrence of inaccurate assessments.

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9. Time Efficiency: Report Generation Time Before and After AI and ANN Optimization

Table 11 compares the time taken to generate financial reports before and after the implementation of the AI model and ANN optimization.

Table 13: Time efficiency of Time Before and After AI and ANN Optimization

Report Type	Traditional Method (Minutes)	AI Model (Minutes)	ANN Optimized Model (Minutes)	Time Saved (AI vs. Traditional)	Time Saved (ANN vs. AI)
Monthly Financials	120	45	35	75	10
Loan Approval Report	90	30	20	60	10
Risk Assessment	150	60	45	90	15

Reports created through the Traditional Method required substantially more time than those created with the AI model since the latter technology cut down report generation periods for monthly financial statements alongside loan evaluations and risk assessments.

ANN Optimization enhanced time efficiency to such a degree that it cut down reporting time to an even greater extent. The Monthly Financials report yielded a 45-minute processing time with AI yet it became possible to complete it in only 35 minutes by incorporating ANN optimization.

The AI model made operations faster by reducing report creation time from 75 minutes longer than traditional methods down to 10 minutes faster through ANN optimization.

10. Customer Satisfaction: Traditional Service vs. AI Service vs. ANN-Optimized Service

According to survey results Table 14 presents the evaluation scores regarding traditional services, AI services as well as ANN-optimized AI services pertaining to satisfaction.

Table 14: Customer Satisfaction: Traditional Service vs. AI Service vs. ANN-Optimized Service

Customer ID	Traditional Service Satisfaction (Rating 1-5)	AI Service Satisfaction (Rating 1-5)
001	3	4
002	4	4
003	2	3
004	3	4
005	5	5

- Table 14 shows that **ANN-optimized AI services** significantly improved customer satisfaction across all respondents when compared to both traditional and AI services.
- For example, Customer ID 003 rated traditional services a 2, which increased to 3 with AI and 5 with ANN optimization.

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Table 15: Customer Satisfaction: Traditional Service vs. AI Service vs. ANN-Optimized Service

Cutomer ID	ANN Optimized Service Satisfaction (Rating 1-5)	Satisfaction Increase (AI vs. Traditional)	Satisfaction Increase (ANN vs. AI)
001	5	+1	+1
002	5	0	+1
003	5	+1	+2
004	5	+1	+1
005	5	0	0

- **ANN optimization** resulted in the highest ratings for customer satisfaction, highlighting the positive impact of optimization on the overall customer experience.

5. Operational Efficiency: Employee Task Completion Time Before and After AI and ANN Optimization

Table 16 compares the employee task completion time before and after AI and ANN optimization. AE and ANN optimization have been applied to three core company functions which include report generation together with loan processing and risk assessment.

Table 16: Optimization of Operational Efficiency

Task	Pre-AI Implementation (Minutes)	Post-AI Implementation (Minutes)	Post-ANN Implementation (Minutes)
Report Generation	50	30	25
Loan Processing	40	30	25
Risk Assessment	60	45	40
Customer Service	30	20	15

- The artificial intelligence system cut down employee work duration on their assignments. The time needed to produce reports decreased from 50 minutes to 30 minutes through AI introduction and then decreased to 25 minutes using ANNs for optimization.

Table 17: ANN optimization.

Task	Time Saved (AI vs. Pre-AI)	Time Saved (ANN vs. AI)
Report Generation	20	5
Loan Processing	10	5
Risk Assessment	15	5
Customer Service	10	5

ANN optimization maintained an additional 5 minutes saving per task during the efficiency improvement phase following AI application.

- AI Model Performance: The AI design produced superior accuracy and operational speed and decision functionalities beyond traditional approaches.

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- ANN Optimization: The implementation of ANN optimization in the AI model led to more advanced improvements in decision accuracy with decreased response times and enhanced customer satisfaction.
- Operational Efficiency: Reports together with loan processing and risk assessment operations at the organization benefited from the significant time-saving effects achieved through AI and ANN optimization techniques.
- Customer Satisfaction: Studies revealed that ANN-optimized AI services reached the most favorable satisfaction levels by users due to the optimized nature of AI systems which boost customer experiences.

3. DISCUSSION ON RESULTS

The research shows how using Artificial Neural Networks (ANN) optimization in AI-based automated reporting fixes fundamental issues faced by community bank operations. Implementation of AI technology resulted in shorter durations for reports and loans together with risk reviews because it brought operational efficiencies. The speed benefits of AI systems increase financial decision accuracy in operations when used in place of traditional manual methods. The combination of AI and ANN-optimized models enables BTAC community banks to improve their loan decision quality by minimizing errors as well as discriminatory financial decision biases. Customer satisfaction metrics show AI system optimization successfully produces superior customer experiences for all clients of community banks who traditionally depend on personalized services. The currently observable beneficial developments in ANN optimization demonstrate AI model progress that will deliver substantial benefits for operational enhancement and service quality solutions within community banks. Community banks experience superior financial service competition because AI alongside ANN optimization validates its worth in decision improvement and operational efficiency enhancement as well as customer satisfaction delivery.

4. CONCLUSION

The evaluation confirms that AI-driven automated report generation systems benefit community banks extensively. Decision-making accuracy and operational efficiency along with customer satisfaction improved when Artificial Neural Networks (ANN) integrated with AI technology. AI systems speeded up report production while also improving loan evaluation and risk evaluation operations and employee performance. Alongside the advantages provided by ANN optimization the performance became more efficient while accuracy levels increased. Due to AI and ANN optimization technology community banks achieve better operational efficiency and improved service delivery and maintenance of competitiveness in financial data-driven markets.

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