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## Conceptual study on e-banking systems and customer satisfaction using deep learning and blockchain

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**Abstract:** The rise of digital payments enhances global internet and mobile usage. However, there are still issues with customer satisfaction in mobile e-banking. This study examines how mobile banking service quality impacts customer satisfaction, detects hackers, and offers solutions for improvement through blockchain integration. This study compares artificial neural network performance with ML models like naive Bayes and XGBoost. The validated data is first sent to cloud for verification, and then securely stored on blockchain to protect customer information. The study uses ANN, a DL model to reduce hacking and ensure secure transactions for enhanced security. The proposed approach is implemented using Python platform and Ethereum tool. The study shows that the ANN model outperforms the ML models in terms of security, achieving an accuracy rate of 99.44%, making the proposed model ideal for e-banking applications. This approach not only enhances security against hacking but also builds customer trust and satisfaction.

**Keywords:** artificial neural networks; ANNs; blockchain; customer satisfaction; deep learning; DL; e-banking; machine learning; ML.

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## 1 Introduction

The rapid progression of information technology has enabled bank users to maintain a secure and stronger connection to their accounts through the internet and mobile devices. With this advanced technology, banks have used e-banking and mobile banking to involve customers and bankers in transactions for customer satisfaction (Haider et al., 2024). E-banking is the facility of banking services via electronic networks like the internet, mobiles, and automated teller machines (ATM) cards, which revolutionised the banking industry through the accessibility of banking transactions anywhere and anytime with mobile phones. Mobile payment includes many applications, such as mobile banking, electronic wallets, Google Pay, Apple Pay, Paytm, and PhonePe, making customer transactions easy (Almansour and Elkrghli, 2023; Vidani, 2024). These applications satisfy customers by saving the time and effort of a payer without physically visiting the bank for any services 24 hours a day (Sharma, 2024; Rozie et al., 2023). Private companies and public sectors also use e-banking services to manage financial transactions, employee salaries, and other services. Small online businesses generally use e-banking services to pay and receive online transactions. E-banking enhances the financial control of the user and displays the actual time and history of transactions. Customer satisfaction in e-banking transactions is much more needed to understand the user satisfaction of various levels of customers (Chen et al., 2022; Rahman et al., 2023). Deep learning (DL) and blockchain (BC) technologies enhance the security of e-banking services.

Machine learning (ML) models like logistic regression, decision trees, and random forests (RFs) were used to evaluate and predict mobile payment behaviour in the financial sector (Zhang, 2024). The structural equation model (SEM) technique based on partial least square (PLS) demonstrates that mobile payment involvement significantly and positively impacts customer satisfaction and repurchase intention (Putri et al., 2023). BC implementation in digital payment enhances the trust in accepting digital payment systems. Integrating BC technology and digital payment systems provides a transformative revolution in the digital payment sector (Norbu et al., 2024). The permissioned BC-based system for the financial sector is working based on Istanbul Byzantine Fault Tolerance (IBFT) to solve the single point of failure and transparency problems (Ahmed et al., 2021). In the proposed study, we analyse the continued use of mobile banking and detect fraudulent access to online money transactions. This study also aims to analyse customer satisfaction with mobile banking using integration of DL techniques with a BC approach that helps to identify uncertain and undetected attacks and improve the security level of mobile banking applications.

The contributions of our work are summarised as follows:

- We propose a DL approach using the artificial neural network (ANN) model and BC approach to identify hackers during mobile banking transactions. The proposed DL approach prevents hackers or attackers from entering the user's device, and BC is involved in more secure transmission using a distributed ledger technique.
- The network intrusion detection dataset, which includes 42 qualitative and quantitative patterns gained from both normal and attackers, is used to detect attackers.

- To propose an approach for higher customer satisfaction in the e-banking structure, we have surveyed over 300 beneficiaries and collected responses related to the satisfaction level of various services provided by e-banking applications.

The remaining portion of the article is organised as follows. Section 2 explains customer satisfaction based on existing works in the literature. In Section 3, the proposed methodology is explained. In section 4, the ANN model for customer satisfaction is analysed along with the BC tool used for providing security to e-banking applications, and the results are discussed. In Section 5, the significance of the proposed work is summarised.

## **2 Literature survey**

This section analyses the study of customer satisfaction in e-banking based on various methodologies. Yesitadewi and Widodo (2024) introduced a method for finding customer satisfaction using the SEM with 218 responses from a sample. This study needed further improvements in customer satisfaction and service quality. Patel et al. (2024) suggested a partial least squares structural equation model (PLS-SEM) to influence the service quality of customer satisfaction with 800 respondents who availed of e-banking services. This research depended only on the information given by the participants themselves. Errors and prejudices might not have influenced the work and no more analyses were performed from the collected samples. Feliciano et al. (2024) collected the data via a direct survey distributed to the customers. The quantitative methodology examined the hypothesis through a dataset comparison of 280 customer responses. The PLS-SEM technique, which runs through SmartPLS 3.2.8 software, was used for this analysis. It was also a single branch, limiting the generalisability of the findings to other regions or branches. Chungu and Phiri (2024) proposed an E-service quality framework directed by a qualitative approach using closed-ended questionnaires managed face-to-face to 120 customers in the 164-sample size. The study needed further improvements in addressing customer queries and problems. Bashir et al. (2023) utilised a sampling technique and a self-administrated questionnaire to evaluate the service quality and customer experiences on the level of satisfaction in e-banking customers. However, the dataset is only designed for binary classification between normal and fraudulent transactions.

To detect suspicious patterns in real-time transactions, Karthick et al. (2024) proposed a technique for unified payment interface (UPI) deception and scams using DL and ANN. This study examines transaction data and user behaviour patterns using convolutional neural networks (CNN) and recurrent neural networks (RNN). Le et al. (2024) developed DL models BERT and Bi-GRU to extract the sentiments from reviews tailored for the distinct of the Vietnamese language. This research utilises a relatively small dataset. Karim et al. (2023) examined the impact of BC mobile payment services on customer loyalty intention by service quality, privacy and security, and customer satisfaction. This study offered better quality customer service and ensured security and safety. However, this study faced limitations due to limited BC payment services. Singh et al. (2024) proposed that ML algorithms logistic regression, RF, support vector machine (SVM), and XGBoost algorithms can be validated with and without SMOTE. Even here,

we found the dataset is with skewed data. It was difficult to interpret complex models like neural networks, making it hard to understand why certain predictions were made. In the work proposed in Gill et al. (2023)], an approach has been discussed with SVM, KNN, and RF methods. SVM was detected with the highest accuracy of 98.74%, which was much superior to the other two methods. A fraud detection dataset was used to identify the frauds. To complete the training process, a lot of processing power and specialised hardware like a powerful graphics unit (GPU) were needed (Xie, 2023). Vannini et al. (2023) introduced an anomaly detection risk management technique, using the triage optimisation model. Socio-demographic (age, nationality, profession, and income), seniority of the client relationship, product usage (saving, investment accounts, and mortgages), and relationship to other customers (shared accounts, spouse, and family) – these features cannot be considered because of the data limitations and constraints. However, the existing models face the problem of customer satisfaction issues like failure transaction data, dataset-related issues, and incompleteness of model training. We introduce DL and BC-based approaches in secure e-banking to overcome the existing gaps. A summary of customer satisfaction is given in Table 1.

**Table 1** Analysis of the customer satisfaction in e-banking

<i>Reference</i>	<i>Method</i>	<i>Dataset</i>	<i>Results</i>	<i>Limitation</i>
Singh et al. (2024)	XGBoost with and without SMOTE	Kaggle website customer churn dataset	83%	Access to large datasets is restricted
Gill et al. (023)	SVM	Fraud detection dataset	98.74%	Training incompleteness
Xie (2023)	XG Boost	Transaction history dataset	99.93%	The failure transaction data was also presented here.
Vannini et al. (2023)	Risk management method	Transaction history dataset. Triage optimisation	95.5%	It does not consider some crucial data.

### 3 Proposed methodology

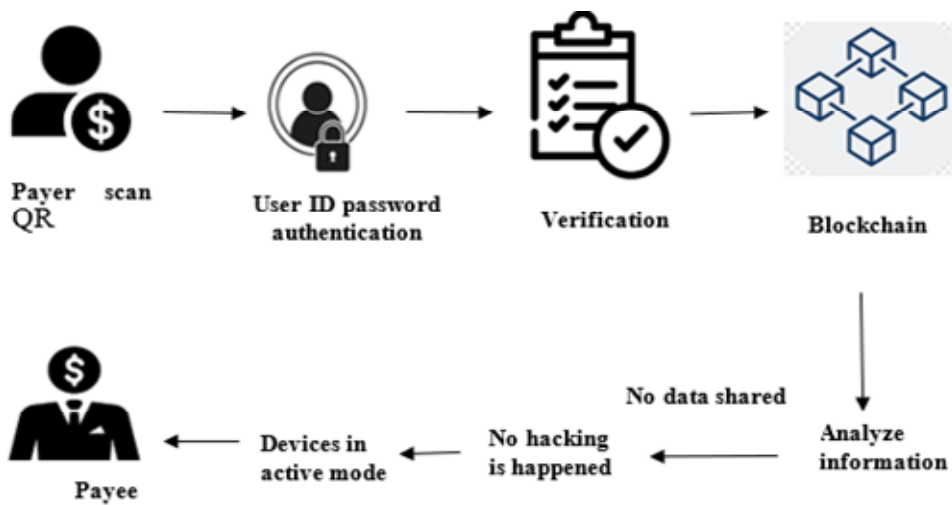
#### 3.1 Deep learning

DL (Huang et al., 2020) can detect suspicious patterns, passwords related to money laundering, and other illegal actions to strengthen transaction security. The DL algorithms can detect anomalies or irrelevant behaviour in data, such as fraudulent acts or irregular events. In e-banking and financial institutions, these algorithms help to manage risk by identifying potential credit, market, or functional risks. It helps to increase efficiency, accuracy, and precision in multiple aspects of life and industry.

Figure 1 illustrates the proposed conceptual framework of customer satisfaction in mobile banking. When the payer scans the payee's quick response (QR) code or enters any random number, the payer's mobile can validate the provided information and user

details (user ID, password, authentication). The information provided by the customer is sent to the cloud. Cloud computing verifies the payer and payee’s provided details. Once the cloud validates the given details, the request is shared with the BC, and then the verified data obtained from the cloud is analysed. After completing the verification process, the BC offers immutability, i.e., no customer’s confidential data can be shared with other devices. The payer can perform operations on their mobile phone, such as mobile payment, online shopping, viewing transaction history, and checking balance amount availability in their mobile wallet. Finally, the DL method is applied for attack detection and improving the security level of the mobile banking application. This ensures that no hacker can enter a user’s mobile device while he is making any transaction.

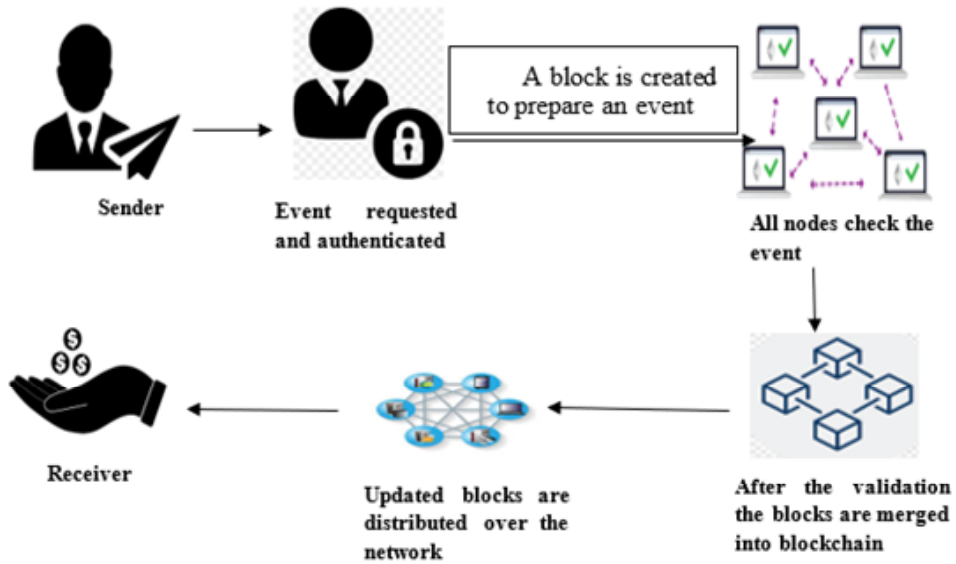
**Figure 1** Conceptual framework of customer satisfaction in e-banking



### 3.2 Blockchain

BC (Javaid et al., 2022) is a secure distributed ledger containing the previous blocks’ cryptographic hash, time and date, and detailed transaction information. This is a decentralised database technology designed to support electronic assets. In a tamper-proof manner, BC permits multiple parties to transact more securely, share important information, and combine their resources. The information stored within the BC is shared between several computers, making it decentralised and highly secure without any vulnerability. BC technology, enabled here, is a rotationally decentralised system that makes transactions between mobile applications on a network safe and impenetrable. Figure 2 shows the working process of BC technology in mobile transactions to enhance the security of transactions. Here, the event means information. Node is a device-stakeholder two-of-a-kind that participates in running the protocol software of a decentralised network called a BC node. Rather than relying on a central entity, nodes collaborate to establish the governing infrastructure of a BC.

**Figure 2** Framework illustrating BC in e-banking (see online version for colours)



*3.2.1 Processing steps involved in the BC approach*

Record the user transaction: BC transaction distributes an action of tangible or intangible data from one party to another in the BC network. At the time of the transaction, the BC has to investigate the verified data provided from the cloud.

Agree with distributed service: During other bulk transactions through BC, the current transaction arrives after successful authentication and agrees with the decentralised distribution of the BC service.

Hook up the blocks: once the candidates have received consensus, the BC transactions are updated into the corresponding ledger phase. Among other transactions, an encryption hash is added to the new block. The links between the blocks and chains are deeply secured, and the data cannot be tampered with.

Share the ledger: the most recent central ledger document is distributed from the system to all applicants.

*3.3 DL strategies in e-banking*

*3.3.1 Machine learning*

The main emphasis of ML is utilising data and methodologies to permit artificial intelligence (AI) to imitate the way humans learn, thereby improving its performance over time. ML algorithms are computer models that allow computers to recognise the content, make predictions, or make data-based decisions. ML algorithms are used for many applications, including photo and speech recognition, natural language processing, system recommendation, and detecting fraud activity. This study covers ML algorithms such as Naive Bayes classifiers and XGBoost and for e-banking applications to compare the benefits of DL approaches over ML algorithms.

### 3.3.2 Naive Bayes classifier

The naive Bayes classifier (Ningri et al., 2023) is a probabilistic ML algorithm based on the Bayes theorem. It is specifically famous for its text classification tasks, such as spam identification and sentiment analysis, but it can apply to various classification problems. Naive Bayes trusts Baye's theorem, which elaborates on the chance of an action based on first-attention knowledge of conditions that might be linked to the event. This algorithm calculates the chance of a specific class given a set of features. It is a strong baseline model in classification tasks. This ML classification technique gives an 89.48% accuracy rate. The confusion matrix has two classes: normal and attack. The row indicates predicted labels, and the column indicates true labels. The confusion matrix table is used in classification to measure the model performance. It allows us to calculate several model performance evaluation matrices.

### 3.3.3 XG boost algorithm

The XG Boost (Hajek et al., 2023) method is a robust ML algorithm that can help you understand your information and make the best decisions. XG boost stands for extreme gradient boosting. It is the performance of gradient-boosting decision trees. To ensure the acquired performance evaluation, the robustness of the detection methods of unauthorised persons using mobile payment information has to be verified. The XG boost algorithm gives an accuracy rate of 98.17%. Compared to the Bayes classifier, it provides the highest security in mobile transactions.

## 3.4 DL approach for fraud detection during e-banking transaction using ANN model

An ANN is a DL model inspired by the human brain's neural structure. DL models can recognise intricate patterns in images, text, audio, and other data to produce precise conclusions and predictions. It comprises interconnected nodes organised into layers varying from single to multiple layers. Through these nodes, the data flow and the network adjust the connection strength during training to learn from the data. This enables us to identify patterns, make predictions, and handle various tasks in ML and AI. It is discovered that the ANN algorithm (Nosrati et al., 2024) is extremely good in the field of prediction problems. Compared to ML algorithms like XGBoost, and Bayes classifier it gives a higher accuracy rate and a more comfortable transaction. The ANN model provides a more secure transaction to the customer.

## 3.5 Integration of BC and DL

Nowadays, DL and BC approaches have achieved successful attention for a greater security mechanism. This is due to the high possibility of creating accurate decisions and information security. Data origin characteristics are transparency, traceability, and loyalty gained by a more centralised server-based DL method. The BC technology is essential for recycling and loyalty sharing of DL methods. Similarly, inspection, data validation, authentication of outcome, proof, identity of ownership, usage, and assurance of fairness are the main motives behind the integration of BC and DL (Shafay et al., 2023). This study examines the advantages of merging DL algorithms with BC technology. By using

BC technology, there is no delay in transaction time. BC provides a more secure transaction mechanism when the server is busy with parallel tasks. Sometimes, transaction failure happens due to the server being dumped with increasingly overwhelming tasks. BC is used to avoid transaction failure with the help of nodes, find attackers, and protect user transactions. With the help of the proposed approach, hackers cannot enter the customer’s device at the time of the transaction, view transaction history, shop online, pay bills, etc.

## 4 Results and discussion

This section includes a thorough analysis of the proposed work, in terms of ANN approach for fraud detection and the BC platform for customer anonymity protection.

### 4.1 Dataset description

The dataset for analysing the hackers during e-transaction is shown in Figure 3.

**Figure 3** Network intrusion dataset for analysing the hackers during e-transaction (see online version for colours)

Δ protocol_type	Δ service	Δ flag	# src_bytes	# dst_bytes
tcp	http	SF	62.8m	0
udp	private	REJ	0	0
Other (1043)	Other (9917)	Other (3819)	0	0
tcp	http	SF	300	440
icmp	ecr_i	SF	520	0
udp	private	SF	54	51
tcp	http	RSTR	76944	1
tcp	smtp	SF	720	281
tcp	http	SF	301	19794
udp	private	SF	1	1
tcp	private	REJ	0	0
tcp	imap4	RSTO	0	44
tcp	http	SF	209	12894
tcp	ftp	SF	220	688
udp	domain_u	SF	43	71

A network intrusion detection dataset from the Kaggle datasets repository is used in this research. Data was collected during TCP packet transmission, starting and ending simultaneously between the data flows to and from a source IP address to get a target IP address under some well-defined protocol. Every connection is named as either normal or an attack with exactly one specific attack type. Each connection record consists of about 100 bytes. For every TCP/IP connection, 42 quantitative and qualitative features are obtained from normal and attack data, meaning three qualitative and 38 quantitative features. The class variables are named as normal and anomalous. The dataset contains

22,544 rows and 41 columns. This dataset is used to detect the attackers during the transaction.

- Dataset link: <https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection/data>.

#### 4.2 Customer satisfaction in e-banking

Customer satisfaction in e-banking provides a deeper insight into the banker’s products and services and the customer’s usage level. The financial sector could launch innovative attributes that meet customer expectations by grasping the components customers cherish and need in their digital banking interconnections, ensuring engagement and satisfaction (Scientific, 2024). In addition, the e-banking policy increases the all-inclusive user experiences that provide insights into customer engagement. The achievement of any new technology highly depends on customer perception and satisfaction during the service interaction. The adoption of mobile payment services only occurs when customers have a good perception of them and are satisfied with their services. By knowing the highest transaction time, well-known services, and shared user preferences, banks can provide resources more justifiably, increase service delivery, and decrease operational costs.

**Table 2** The sample dataset information on customer satisfaction in e-banking

<i>E-banking application</i>	<i>Usage of e-banking application</i>	<i>Services access using e-banking</i>	<i>Convenient using e-banking</i>	<i>Bothered about e-banking</i>	<i>Satisfaction level</i>
Gpay	Every day	Money transaction	Yes	Yes	Satisfied
Gpay, Paytm	Once a week	All of these	Yes	Yes	Satisfied
Gpay, Phonepe	Every day	Money transaction	Yes	No	Highly satisfied
Gpay, Paytm	Once a week	All of these	No	Yes	Satisfied
Gpay, Phonepe	Every day	Bill Payment	Yes	No	Highly satisfied
Gpay, Paytm	Every day	All of these	Yes	Yes	Satisfied

To learn customer satisfaction for e-banking services, we created a dataset using the direct sampling method, as there are currently no datasets available for e-banking services and customer satisfaction. Most of the data available so far is only for banking services; however, as most of the population has moved to digital transactions, it is necessary to study e-banking services. We created our questionnaire dataset and shared it for a survey on social media. We received a sample of 300 respondents. The questions were related to e-banking customer satisfaction. Customers answered the questions based on their experience with e-banking services and their related needs. A portion of the dataset about customer satisfaction is listed in Table 2.

From Table 3, Out of 300, 274 people use mobile banking apps, the full-time employed people mostly use these apps for cash transactions, and it indicates the person must use the mobile application once a week for money transactions, bill payments, or any other purpose. The remaining reports are shown in the following graphs.

Figure 4 graph shows the usage convenience of mobile banking. Out of 300 respondents, 272 customers said yes, and the remaining customers said no. Based on this survey, most of the people said convenience in using mobile applications for money transactions.

From Figure 5, it illustrates the bother of using mobile transactions. This also makes clear of e-banking customers' fear towards using mobile applications. As 153 respondents said yes to the fear of fraud and 143 said no to the fear of fraud at the time of cash credit/debit, the fraud fear is almost equal.

**Table 3** Number of respondents based on individual questions

Are you using e-banking?		Those who use e-banks, based on occupation					Usage of mobile bank			
Yes	No	Fulltime Job	Part-time job	Homemaker	Self-employed	Student	Once a week	Everyday	Once a month	Never
274	26	139	26	37	45	54	173	85	29	13

Initially, a few questions contained personal information about the person who uses e-banking apps. Further questions are as follows: Are you using mobile banking? Have you used any of the mobile payment applications like Gpay, phonePe, or Paytm? What services you access using e-banking, such as money transactions, online shopping, bill payment, mobile recharge, and DTH recharge? Are you comfortable using e-banking? Are you afraid of fraud at the time of mobile transactions? Are you satisfied with the level of service provided by the e-bank?

**Figure 4** A graph of usage convenience of e-banking (see online version for colours)

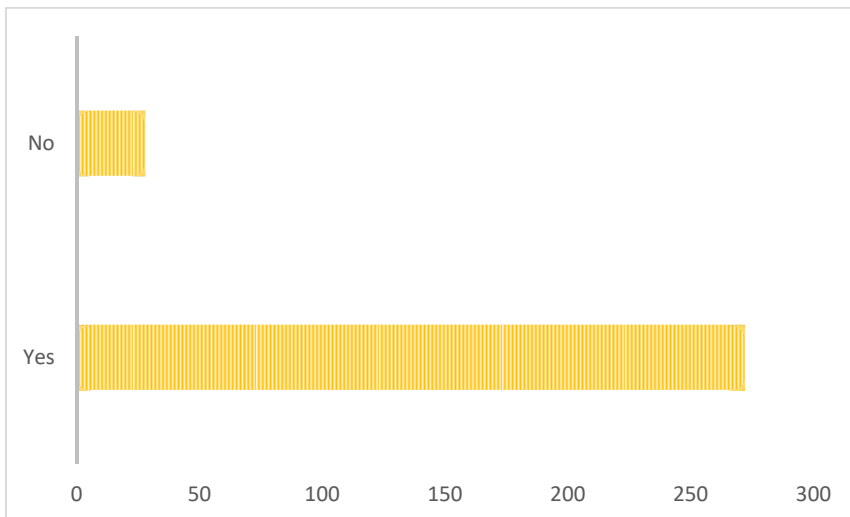
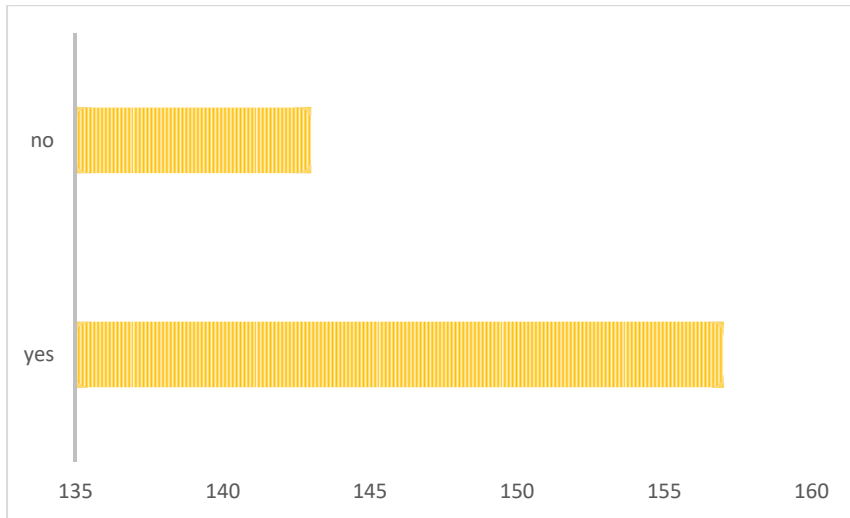


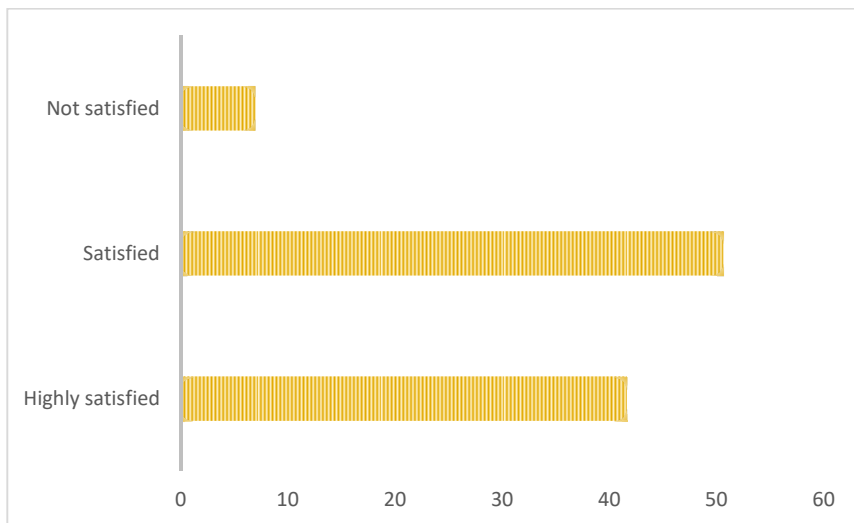
Figure 6 graph shows the satisfaction level of the service provided by e-banking applications. 51.66% of respondents were highly satisfied, 41.66% were satisfied, and

only 7% were not satisfied. Almost 97% of customers mentioned being satisfied with using e-banking; however, they fear about their data and the finances they maintain in their bank.

**Figure 5** Fear of fraud at the time of transaction (see online version for colours)



**Figure 6** Are you satisfied with the service provided by e-bank (see online version for colours)

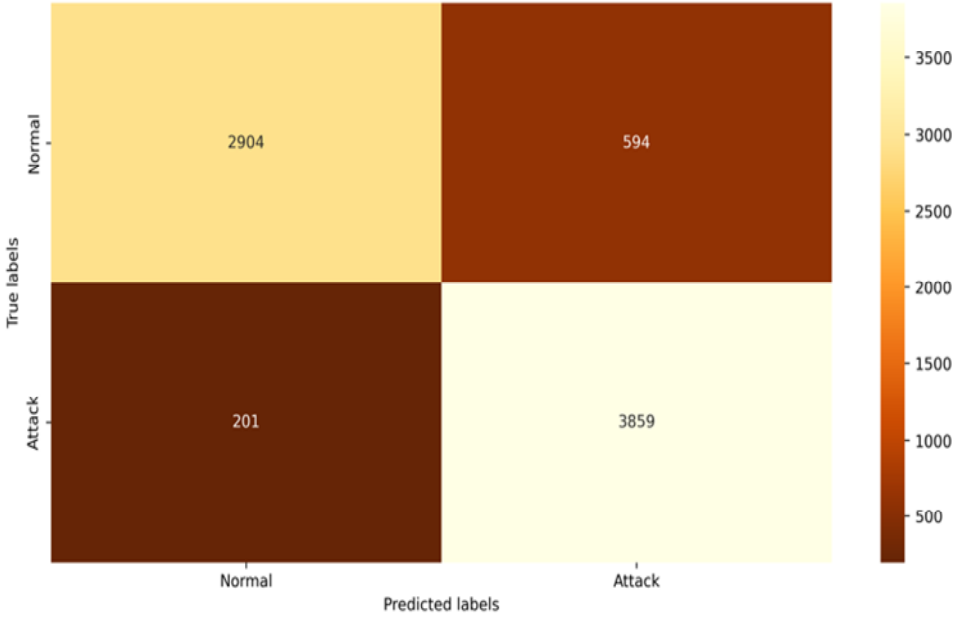


### 4.3 Performance analysis of the proposed model

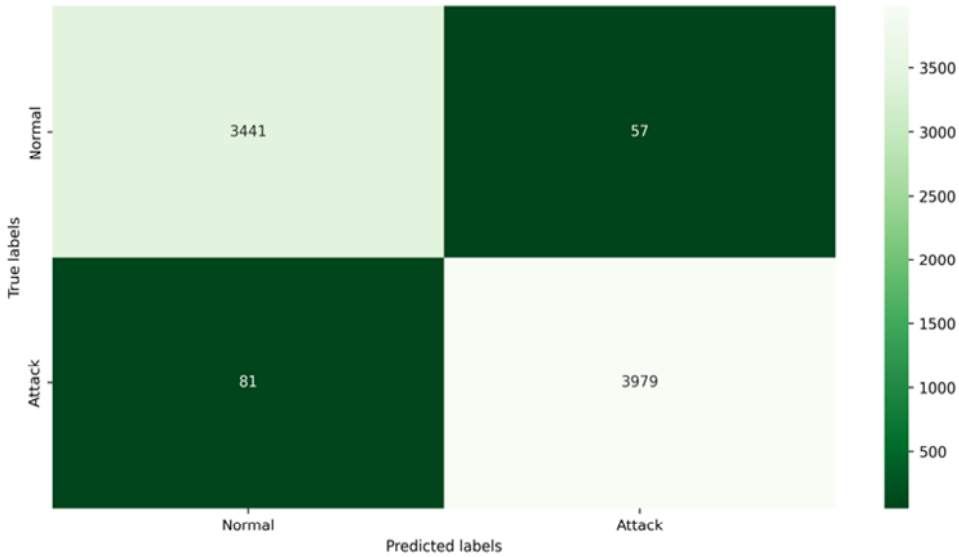
Table 4 analyses the proposed models' performance metrics, which show the performance of naïve Bayes, XG boost, and ANN models. Table 4 shows the proposed model's accuracy, precision, sensitivity, specificity, F\_measure, Matthews correlation

coefficient (MCC), negative predictive value (NPV), false positive rate (FPR), and false negative rate (FNR).

**Figure 7** Performance of the proposed model’s confusion matrix, (a) confusion matrix of the Naïve Bayes classifier (b) XG boost classifier (c) ANN model (see online version for colours)

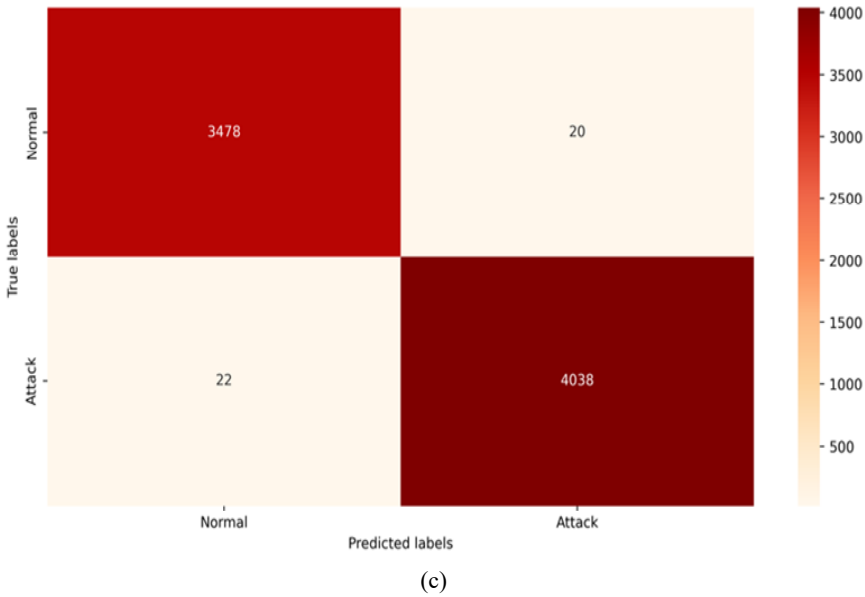


(a)



(b)

**Figure 7** Performance of the proposed model’s confusion matrix, (a) confusion matrix of the Naïve Bayes classifier (b) XG boost classifier (c) ANN model (continued) (see online version for colours)



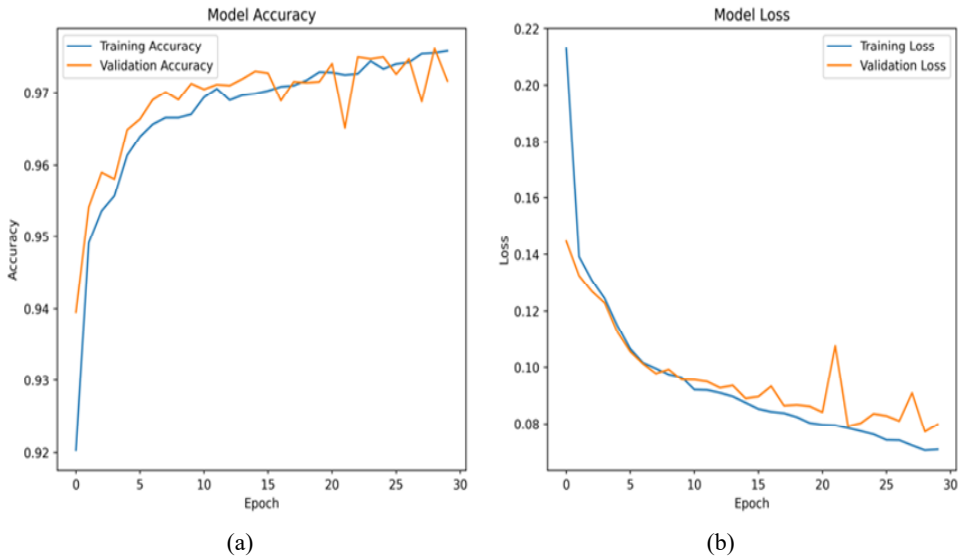
**Table 4** Performance analysis of the proposed model

Metrics (%)	Naïve Bayes	XG boost	ANN
Accuracy	89.48	98.17	99.44
Precision	86.66	98.58	99.50
Sensitivity	95.04	98	99.45
Specificity	83.01	98.37	99.42
F_measure	90.67	98.29	99.48
MCC	79.12	96.33	98.88
NPV	93.52	97.7	99.37
FPR	16.98	1.62	0.57
FNR	4.95	1.9	0.54

Figures 7(a)–7(c) demonstrate the confusion matrix which evaluates the classifier model using two classes namely normal and attack. This shows the true positive and true negative classification percentages for each class. Each row denotes the predicted labels and each column signifies the true labels.

Figure 8 shows the performance graph of model accuracy and model loss. We trained our proposed model with 30 epochs. Figure 8(a) shows that the difference between the training and validation loss, and Figure 8(b) shows training and validation accuracy, is less small. This proves that the proposed model performs well on unknown data and generalises well.

**Figure 8** The ANN model’s accuracy and loss curves in terms of training and validation, (a) accuracy graph (b) loss graph (see online version for colours)



#### 4.4 Performance comparison of ML and DL algorithms

Performance comparison between ML models such as XGBoost, and Bayes classifier and the DL models using ANN depends on the data used, the complexity of the problem, and the evaluation metrics used. We compared the proposed ML algorithms. This paper compares the ML and DL algorithms to get the best accuracy rate for e-transactions. The performance comparison between the ML and DL is presented in Table 5. The goal of performance comparison in various ML and DL models of e-banking transactions is to determine the effectiveness of accurately classifying transactions.

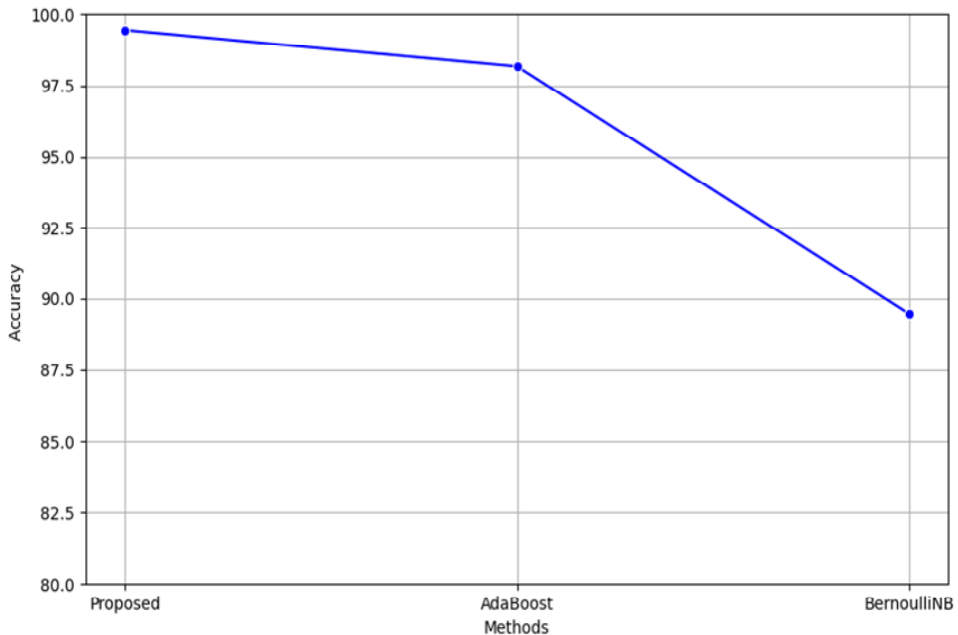
Table 5 demonstrates the comparability analysis of the ML and DL algorithms in terms of accuracy, precision, specificity, and F1 score. ML algorithm was as Naïve Bayes and XG Boost and the proposed DL algorithm was ANN. It shows that the proposed algorithm obtained accuracy values of 89.48, 98.17, and 99.44 (%), precision values of 86.66, 98.58, and 99.50 (%), specificity values of 83.01, 98.37, and 99.42 (%), and F1 score values of 90.67, 98.29, and 99.48 (%). Thus, the highest accuracy using ANN models in DL with 99.44%. This algorithm gives more secure transactions than other ML models.

Figure 9 illustrates the visual performance comparison of ML and our proposed methodology based on the accuracy values.

**Table 5** The performance comparison of ML and DL models for e-banking

Algorithms	Accuracy (%)	Precision (%)	Specificity (%)	F1 score (%)
Naïve Bayes	89.48	86.66	83.01	90.67
XG Boost	98.17	98.58	98.37	98.29
ANN	99.44	99.50	99.42	99.48

**Figure 9** The performance comparison of ML and DL based on accuracy (see online version for colours)



#### 4.5 Discussion

Thus, the study aims to learn and understand customer satisfaction with e-banking services to improve the e-banking applications availed by bankers. All over the world, mobile phone and internet banking platforms have risen heavily. More people are using mobile applications to access banking services comfortably because there is an increasing infiltration of smartphones and high-quality network connectivity. Customers through their smartphones can access internet banking. E-banking modes have various kinds of transactions; these are bill payment, mobile recharge, DTH recharge, online purchases, online food order payment, malls, supermarkets, petty shops, and fund transfers. These services contribute to their famous convenience and easy accessibility. The evaluation of customer satisfaction decides the level of fulfilment of customers have with a company's providing services and ability. The customer satisfaction data are surveys and social media ratings, which can assist an industry in determining how to enhance or change its products and services. Based on the market search, survey, and data analytics to earn insights about product development, marketing strategies, and customer relationship management efforts, the company can analyse customer satisfaction/customer behaviours.

Customer satisfaction in mobile transactions is to be gained from the comparison analysis using ML models and DL. In ML XG boost and Bayes classifier are used. In DL, ANN algorithm is used. In this comparison, DL-based ANN gives the best accuracy rate which assures, secure transactions to the customers. In rural areas, people panic about using mobile transactions because of the fear of hackers. E-banking transactions are famous worldwide, but some people are not comfortable with this transaction mode; they

are visiting the bank physically because they could not trust internet transactions because of transaction failure and scams. Sometimes the money has been debited to the account but the receiver cannot get their cash credited, hence some beneficiaries still have no trust in this mode of transaction. To reduce this risk, the DL model and BC approach are integrated, which helps to detect the attackers and give a secure transaction. The DL model also provided us with a 99.44% accuracy rate for detecting hackers at the transaction time. This ensures more security in transactions and improves customer satisfaction with e-banking services provided by banks in the public or private sectors.

## **5 Conclusions**

Customer satisfaction with e-banking services improves and spreads the digital sense of financial usage for various applications. Still, there are challenges in educating and reaching people at various literacy and cultural levels. In this study, we analysed the customer satisfaction level and reason for dissatisfaction through a sampling approach. We proposed a DL model with a BC approach for improving the security level of e-banking applications. We compared the various ML algorithms like XG boost, Bayes classifier, and DL algorithm ANN model for developing a secure framework for e-banking, and the ANN model provided better performance parameters. The best understanding of customer satisfaction in e-banking transactions gives significant strategic and operational benefits. It enables the banking sector to provide superior services, such as promotions, improve security, increase trust, and stay relevant in using the current digital banking landscape. This study proves that the ANN model gives customers more secure transactions and satisfaction. In the future, we can improve the model by implementing the model in a real and live transaction environment on a network server.

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Both authors contributed to the conception of the problem setting and overall design of the work. S.T. built the conceptualisation and methodology, K.D. implemented the work, and writing was done by both. This version was revised and improved by both authors, who also read and approved the final manuscript.

## **Declarations**

The research is original and all the figures and tables are created by the authors of this manuscript.

Both authors agree with the submission of the manuscript to this journal and possible publication afterwards.

The authors declare that they have no conflict of interest.

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