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Research Article

The Impact Of Digital Finance On Women In Thanjavur City With Real-Time Data"

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ARTICLE INFO | **ABSTRACT**

Digital financing is a vital component for businesses worldwide. Although there have been significant advancements in digitization in emerging and developing countries, a considerable portion of society, such as small-scale farmers, rural youth, and female farmers, remain excluded from mainstream financial activities.Individuals are being provided with a renewed sense of optimism via the use of machine learning technologies. But, the choice on how to use this cutting-edge technology to lessen human prejudice in loan selection is withbanks or non-banking firms. Hence, the objective of this research is to emphasize the different AI-ML-based approaches used by banking or non-banking entities for financial inclusion and identify the existing shortcomings.This study used systematic literature review techniques to empirically examine current research publications. The aim was to find and compare the most suitable AI-ML-based model implemented by different financial institutions globally. This research utilizes a machine learningframework to do a thorough investigation of the transformational impacts of digital finance on women residing in rural regions.It is crucial to comprehend the varied consequences of technology breakthroughs on excluded people as they transform conventional financial landscapes. This study utilizes machine learning algorithms to examine comprehensive datasets that include financial transactions, socio-economic factors, and behavioural patterns, with a special focus on women living in rural areas.

Keywords: Financial inclusions, Machine learning, Digitalization, AI, Rural region.

Introduction

Financial inclusion refers to the capacity of company owners to get financial goods and services to meet the demands of their consumers or customers (Belotti et al., 2020). The concept encompasses activities like as saving, generating and receiving money, conducting transactions, obtaining credit, and acquiring insurance (Abuhusain, 2020). It is essential for all business organizations, particularly small-scale firms in developing countries. The inclusion facilitates access to loans for small-scale enterprises, enabling them to invest in their operations. Additionally, it facilitates cash preservation, enabling future investments or the ability to respond to unforeseen hazards (Fontes and Gay, 2021). Enhancing financial inclusion facilitates the availability of insurance products and services, which play a crucial role in mitigating risks in enterprises (Aliija and Muhangi, 2017). One essential aspect of effective governance in any nation is the establishment of sufficient financial inclusion plans for small-scale enterprises, aimed at enhancing the production of goods and services, as well as boosting employment rates and improving the overall quality of life.
Located in the central region of Tamil Nadu, among the abundance of cultural heritage and historical significance in Thanjavur, a profound wave of change is revolutionizing the financial sector, with a special focus on empowering its female population. The advent and assimilation of digital banking have resulted in a fundamental change, not only in the way financial transactions take place but more importantly, in enabling women to actively engage in economic endeavours. This research explores the ever-changing field of digital banking and its concrete impact on the lives of women in Thanjavur. It is backed by real-time data to accurately portray the shifting story.
Thanjavur, with its distinctive amalgamation of history and technology, provides an ideal setting to examine how digital banking has acted as a catalyst for promoting women's financial inclusion. This research seeks to

explore the intricate effects of digital financial instruments on women's economic autonomy, decision-making authority, and overall socio-economic welfare, amidst an unparalleled increase in technological progress worldwide (Ampountolas et al., 2021).

By providing a contemporaneous picture of the ongoing transition, the use of real-time data gives this inquiry a dynamic element. Through documenting the struggles, successes, and experiences of women interacting with digital money in Thanjavur, this study aims to make a significant contribution to the international conversation around gender-neutral financial ecosystems.

As we begin this exploration, our goal is to not only acknowledge the progress that has been made but also to identify any obstacles that might impede the complete achievement of the advantages of digital banking for women in Thanjavur. This study looks at the complicated relationship between digital finance and women's freedom in an area where custom and the future meet. It does this by looking at things from the point of view of finance, technology, and culture.

The research seeks to clarify the many ways in which digital finance activities contribute to the financial inclusion, self-determination, and general well-being of women. The study uses prediction models and data-driven insights to try to figure out what makes rural women use digital financial services and how those services affect their ability to make economic decisions.

Combining quantitative analysis with qualitative insights gained from focused rural community interviews and surveys, the approach is unique. Machine learning algorithms are used to identify trends in financial behaviour, reveal possible obstacles to adoption, and forecast the lasting influence of digital banking on women's financial autonomy.

Policymakers, banking institutions, and development agencies should be able to use the study's results to help them make digital finance plans that are inclusive and take gender into account.Moreover, the discoveries might enhance the improvement of current policies, tackling particular obstacles encountered by women in rural regions, and promoting a fairer and more enduring financial system. With the ongoing evolution of digital finance, it is crucial to comprehend its impact on excluded communities to advance inclusive economic development and gender equality.

Literature Survey

According to the World Bank, over 80 nations have implemented digital financial services, including mobile phone use(Aniceto et al., 2020). Consequently, a large number of formerly marginalized and disadvantaged persons are transitioning from using cash for transactions to using formal financial services that provide them with a range of offerings such as transactions, payments, credit, insurance, stocks, and savings (Antunes, 2021). The widespread use of mobile phones and other digital technologies, including artificial intelligence (AI), has led to a noteworthy increase in financial inclusion (Assef and Steiner, 2020). Digital financial inclusion refers to the provision of inexpensive and sustainable financial services to clients(Beck, 2020). The entry of non-financial enterprises in the supply of new technologies employed in digital financial services has brought several advantages to previously excluded clients. However, it has also introduced a variety of hazards that need to be considered (Bennouna and Tkiouat, 2018).

There are some risks in digital finance. For example, there are new contracts between banks and third parties that use agent networks. There are also risks because deposit-like products are regulated differently than real deposits. Finally, there are risks that consumers who aren't familiar with digital finance may have to pay too much or too little, and there are risks that come from using new types of data that can be used in bad ways(Boughaci and Alkhawaldeh, 2018). Nevertheless, specialists assert that the utilization of AI, specifically algorithms, may aid in mitigating some threats. In Industry 4.0, the use of AI is becoming more prevalent. Simultaneously, there is a growing focus on digital financial inclusion, particularly for marginalized groups such as women, youths, small businesses, and other disadvantaged individuals.This research aims to examine the influence of artificial intelligence (AI) on digital financial inclusion. Specifically, it seeks to identify the many ways in which AI might enhance financial inclusion.

The proportion of adult consumers with access to banking and financial services is known as financial inclusion. In 2017, 79.9% of people in the 15+ age group held accounts with financial institutions, according to the Global Findex Survey (Kumar and Gunjan, 2020). This is a significant increase compared to the 53.1% recorded in the last iteration of the study in 2014, and the 35.2% reported in 2011. Approximately 50% of the global adult population, equivalent to 3.5 billion individuals, lack access to traditional banking services or have restricted access to financial transactions. The greatest population of unbanked individuals is found in China, India, Pakistan, and Indonesia, accounting for a total of 1.7 billion people worldwide.

An essential need for achieving financial inclusion is the establishment of a bank account (Leo et al., 2019). Digital payments are becoming more prevalent for financial transactions. Digital financial inclusion, as defined by the World Bank, refers to the use of cost-effective digital methods to provide formal financial services to individuals who are currently excluded or underserved. This includes tailoring these services to meet their specific needs. In simpler terms, it means ensuring that everyone has access to and uses formal financial services through digital means.The success of M-PESA, a payment innovation developed in Kenya, has led to increased interest in digital financial inclusion. M-PESA facilitates digital payments via the usage of mobile money.

Utilizing artificial intelligence (AI) and diverse information and communication technology (ICT) techniques effectively addresses the primary issue of information asymmetry in conventional financial inclusion (Mandala et al., 2012). Digital services provide users with extensive information that might otherwise be inaccessible. This information's availability mitigates information asymmetry between financial organizations and people (Munkhdalai et al., 2019). Key elements of digital financial inclusion include, among others, digital transaction platforms that facilitate clients' ability to conduct payments and hold electronic currency (Biallas and O'Neill, 2020). Another significant feature offered by digital banking is the use of gadgets, such as mobile phones or payment cards that enable clients to transfer information and communicate with digital equipment like point-of-sale terminals.Furthermore, digital financial inclusion entails the presence of retail agents equipped with digital devices that are linked to communication infrastructure, enabling the transmission and reception of transaction information. This activity enables clients to exchange physical currency for electronically stored value, often known as cash-in, or to convert the stored value back into physical currency, also known as cash-out. Digital financial inclusion enables banks and non-banks to provide extra financial services, such as credit, insurance, and savings, to persons who are financially excluded or underserved. This is made possible via the use of digital technologies, such as artificial intelligence (AI).

2.1 Problem Identification

Based on our analysis, it is evident that many research studies have been conducted on financial inclusion, with the following specific goals: (1) Establishing a framework for implementing financial inclusion to alleviate poverty; (2) Assessing various factors (such as social, political, and environmental) that may impact financial inclusiveness; (3) Encouraging adult participation in banking activities to facilitate access to credit facilities; (4) Creating a financial structure that ensures full extension of financial inclusion to impoverished individuals; (5) Prioritizing government efforts to promote the establishment of micro-insurance institutions. We also learned that statistical techniques were used in the Machine Learning methods to make sure those families, low-income workers, women in rural areas, and small business owners could all get financial help.

Based on the conclusion mentioned above, we have decided to use machine learning techniques in this study to effectively preprocess the FI dataset. The objective is to cleanse, verify, and categorize the data, and establish the connection between the necessary properties of the dataset and financial management governance.

The research paper is thereafter structured in the following sequence. Section 3 provides a comprehensive description of the planned study and the machine learning technique used to elucidate the characteristics and risks associated with financial inclusion for women. Section 4 presents the process of preparing the data set and the subsequent outcomes, accompanied by relevant commentary. In Chapter 5, we complete our study with a conclusion.

Proposed Work

3.1 Data Set Preparation

The data was gathered from women residing in rural areas of Thanjavur district using Google Forms and saved in Microsoft Excel in CSV (comma-separated values) format. Upon analysing the data, the missing values in the input file characteristics, as shown in Table 1, were replaced using the Mode approach. In the mode technique, any missing attribute values in numeric form are substituted with the most often occurring value of the corresponding known attribute.

3.2 Research Methodology

Classification is a kind of supervised learning in machine learning. Its objective is to assign predetermined labels or categories to instances, depending on their attributes. Classification is necessary for many real-world situations where it is crucial to make predictions or judgments based on input data. When working with numerical data for classification jobs, it is necessary to follow certain important stages.

- Data collection
- Data Pre-Processing
- Data Splitting
- Model training
- Evaluation

3.2.1 Pre-Processing

Data quality is assessed by evaluating its correctness, completeness, consistency, timeliness, credibility, and interpretability. Data preparation involves four primary tasks: data cleansing, data integration, data reduction, and data transformation shown in Figure 1.

Figure – 1 *Steps Involved in Data Preprocessing*

(A) Data Cleaning

Mean imputation is a frequently used technique for data cleansing. Mean imputation is a technique used to substitute missing values in a dataset with the average value of the available (non-missing) values for that specific attribute. This approach is suitable for numerical attributes and is a simple but efficient solution for managing missing data.

The mean imputation for a feature S with missing values may be mathematically represented as

$$S_{imputed} = \frac{\sum_{i=1}^{n} s_i}{n} \quad (1)$$

$S_{imputed}$ refers to the feature in which missing data have been substituted with the mean. S_i denotes the values of the features that have been seen and are not missing. n represents the whole set of observed values.

(B) Data Integration

Concatenation is a frequently used technique for data integration. Concatenation is the process of merging datasets along a certain axis, either rows or columns, to form a bigger dataset. This approach is especially advantageous when dealing with data that is housed in distinct tables or files that have shared columns.

The mathematical description of concatenation varies according to whether it is performed horizontally (along rows) or vertically (along columns).

Concatenation among Rows

The mathematical model for concatenating two datasets, A and B, along the rows is:

$$Concatenation\ along\ Rows\ C = A \cup B$$

Here, C represents the resultant dataset, while $A \cup B$ signifies the concatenation procedure.

Concatenation among Columns

The mathematical model for concatenating two datasets, A and B, along the columns is as follows:

$$Concatenation\ along\ Columns\ C = [A, B]$$

Here, C is the resulting dataset, and [A,B] represents the concatenation of datasets A and B along the columns.

(C) Data Reduction

Principal Component Analysis (PCA) is a frequently used technique for data reduction. Principal Component Analysis (PCA) is a method used to reduce the number of dimensions in a dataset. It does this by transforming the data from a high-dimensional space to a lower-dimensional one, while still preserving as much of the original variability as it can. This is accomplished by identifying the primary components, which are obtained by linearly combining the original characteristics.

The major components of a dataset, which consists of i observations and j characteristics, are determined by calculating the eigenvectors and eigenvalues of the covariance matrix of the original data. PCA analysis for our input data is given in Figure 2.

Figure – 2 *PCA Component Analysis*

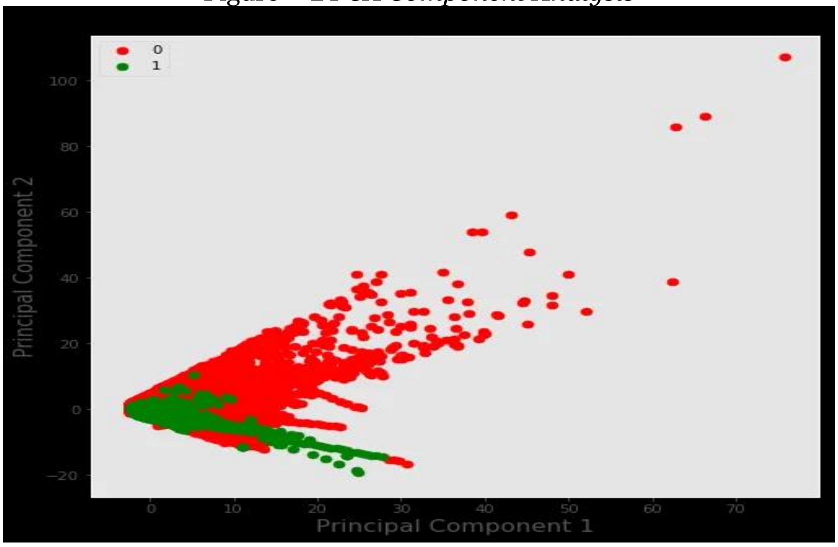


Figure - 3*Class Prediction Based on PCA*

	principal component 1	principal component 2	Class
0	1.571633	-0.675537	0
1	-1.086136	-0.282819	0
2	2.053450	1.077546	0
3	1.150128	-0.427471	0
4	1.143864	-1.342195	0

(i) Covariance Matrix

The covariance matrix Σ is computed for the raw data, where P is the data matrix with each row being an observation and each column denoting a feature.

$\sum = \frac{1}{i-1}\sum_{x=1}^{i}(P_x - P')(P_x - P')^T$c (3)

P is the mean vector

(ii) Eigen value Decomposition

Conduct eigenvalue decomposition on the covariance matrix Σ. The eigenvectors and eigenvalues are acquired:

$\sum v = \lambda v$ (4)

where v is an eigenvector and λ is the corresponding eigenvalue.

(iii) Selecting Principal Component

The primary components consist of the eigenvectors that correspond to the highest n eigenvalues, where n is the desired decreased dimensionality.

$principal\ Component = \{v_1, v_2, \ldots\ldots, v_n\}$ (5)

(iv) Transforming Data

The original data P is then projected onto the lower-dimensional space using matrix multiplication with the chosen primary components V.

$Transformed\ data = PV$ (6)

(D) Data Transformation

The Box-Cox Transformation is a frequently used technique for data transformation, specifically for addressing issues related to non-constant variance and achieving a more consistent distribution of the data. The Box-Cox transformation is suitable for data that displays positive skewness or heteroscedasticity (increasing variability with rising values). It is particularly advantageous when handling data that deviates from the assumptions of normalcy.

The Box-Cox transformation is defined by the following equation:

$$\begin{cases} \frac{y^{\lambda}-1}{\lambda}, & if\ \lambda \neq 0 \\ In(y), & if\ \lambda = 0 \end{cases} \quad (7)$$

y is the original data.
λ is a parameter that determines the type of transformation
The transformation is applied for y>0 if $\lambda \neq 0$ and y>0 for $\lambda = 0$

3.2.2 Data Splitting

A survey was conducted in the rural region of Thanjavur district among women. The survey collected 2,189 responses using a Google form, which was then converted into a suitable model for a machine learning algorithm. From this dataset, 200 characteristics are derived by considering factors such as education level, family economic status, living style, and investment preferences. Subsequently, the machine learning model is introduced for assessment, and the conclusions are derived from the subsequent hypotheses. Lastly, the whole dataset is partitioned into a 60% training set and a 40% testing set.

- **H_{01}:**Implementing digital inclusive finance may mitigate financial exclusion in rural regions and provide a favourable effect on the accumulation of capital among rural women.
- **H_{02}:**The extent of digital inclusive financial coverage might enhance the accumulation of capital by rural women, and there are variations in this regard across different regions.
- **H_{03}:**The level of digitalization in inclusive finance might enhance the accumulation of capital for rural women, and there are variations in this regard across different regions.
- **H_{04}:**The extent to which digital inclusive finance is used might enhance the accumulation of capital among rural women, and this phenomenon varies across different regions.

Table – 1 *Pre-Processing of Input Data*

V22	V23	V24	V25	V26	V27	V28	Class	Vamount	Vtime
0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053	0	0.244964	-1.996583
-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724	0	-0.342475	-1.996583
0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	0	1.160686	-1.996562
0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	0	0.140534	-1.996562
0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	0	-0.073403	-1.996541

3.2.3 Model Evaluation

Support Vector Machines (SVM) is a robust supervised learning method used for applications including classification and regression. Support Vector Machines (SVMs) are very efficient at classifying numerical data. Support Vector Machines (SVM) can accommodate non-linear decision boundaries by using a kernel function. The kernel function transforms the input characteristics into a space with a greater number of dimensions, enabling the identification of a hyperplane that can separate data that is not linearly separable.

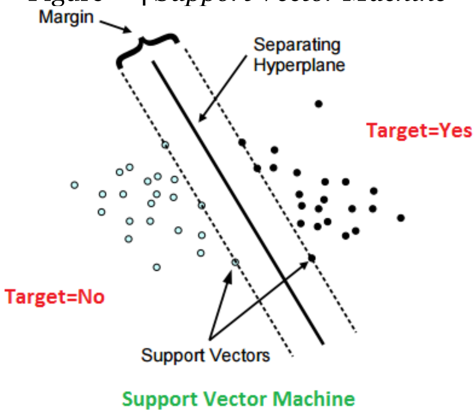
Hyperplane-A hyperplane is a discriminant that partitions data points of one category from another. When considering two dimensions, the object may be described as a line. In the case of three dimensions, it can be referred to as a plane. This pattern continues for higher dimensions.

Margin- The margin refers to the spatial separation between the hyperplane and the closest data point belonging to either class. The objective of SVM is to identify the hyperplane that maximizes the margin.

Support Vector-Support vectors are the data points that are in closest proximity to the decision border. They play a vital role in determining the boundary and the hyperplane.

The Algorithm and workflow of the proposed model isgiven in Algorithm 1 and Figure 5.

Figure – 4 *Support Vector Machine*



3.2.3.1 Algorithm for SVM Classification

Input: Given Dataset with N features
Output: Classified output
Step 1: Select a suitable kernel function based on the nature of the data. Common choicesinclude linear, polynomial, and radial basis function (RBF) kernels.
Step 2: The decision function for a linear SVM is given by f(x)=sign(w.x+b), where **w** is the weight vector, **x** is the input vector, and b is the bias term.
Step 3: The optimization objective is to find **w** and b that minimize the following

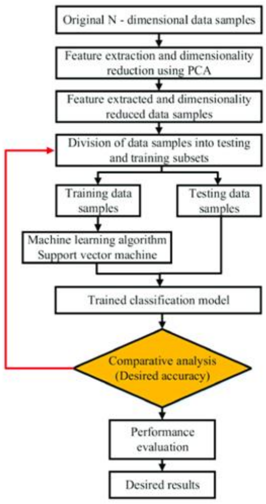
$$\mathrm{Min}_{\mathrm{w,b}} \frac{1}{2} \left||\mathrm{W}|\right|^2 + \mathrm{C}$$
$$\mathrm{Max}(0, 1 - \mathrm{y_i}(\mathrm{w.x_i} + \mathrm{b}))$$

Here, C is a regularization parameter that controls the trade-off between maximizing the margin and minimizing the classification error.
Step 4: Obtain Optimization
Constraints ensure that data points are correctly classified and lie outside the margin.
$y_i(w.x_i + b) \geq 1$ for all i=1,2,....m
Step 6: Calculate Decision Function
The decision function can be expressed as

$$f(x) = \sum_{i=1}^{m} \alpha_i y_i K(x_i, x) + b$$

K is the chosen kernel function.For a new input x, predict the class label y using the sign off(x).

Figure – 5 *Flow Chart of Proposed Methodology*



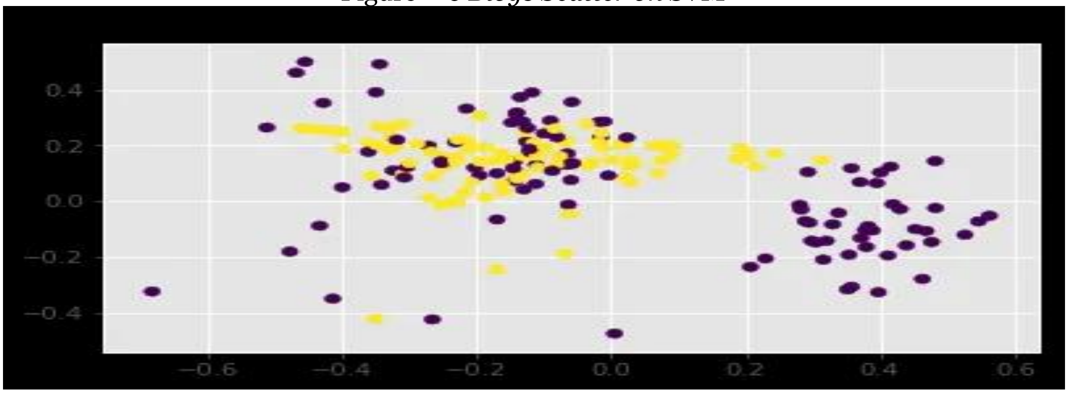
Result Analysis

This section presents a comprehensive examination of the performance of the support vector machine (SVM) algorithm. The analysis focuses on evaluating the recall, precision, and accuracy of the SVM model in accurately classifying instances. The model is implemented using the Python programming language.
The SVM model is most suitable for analysing numerical data. The figure displays the scatter plot of the planned work in the blogs.

(A) Findings based on Choice of investment

When selecting an investment option for rural women, it is important to take into account their distinct requirements, available prospects, and the socio-economic circumstances of the area. Based on the current real-time data, the findings indicate that women residing in rural areas lack a fundamental understanding of investment opportunities primarily because of the absence of digitalization. They prioritize private-based chits above government or assisted initiatives. Approximately 30% of individuals lack awareness regarding banking schemes, particularly those related to deposits and increases in interest rates for older citizens. Between 20 and 25 percent. others get knowledge about such schemes only via the assistance of others such as family or neighbours.

Figure – 6 *Blogs Scatter on SVM*



(B) Findings based on their Profile

A person's socioeconomic and demographic picture shows how well they live, how educated they are, and how powerful they are in society. An examination of the socioeconomic characteristics of rural women in Thanjavur district indicates that a significant proportion of the individuals surveyed are part of the economically active population. Specifically, 45% of the respondents are within the age range of 40-60, while 30% fall within the age range of 20-40. The sample respondents' marital status indicates that a significant majority of them are married (68.3%).However, the educational data indicates that the majority of them possess a fundamental educational background, with qualifications limited to the 10th grade. Only 20% of individuals possess educational qualifications at or above the degree level.Despite the government's strong participation in promoting education among rural women, the persistently poor educational status remains a problem for authorities. The poor educational level is a direct manifestation of the impact of digitalization, with just 6.7% of individuals being engaged in the government sector, while the bulk (65%) work as agricultural laborers. The data indicates that 85% of the sample group had a monthly income below 6000. Compared to the rising cost of goods and necessary commodities caused by inflation, the monthly income of tribal people is insufficient, limiting their capacity to acquire and buy necessities.

(C) Findings based on Access to Digital devices and services

Access to digital technologies and services is a crucial determinant of digital inclusion among individuals. An examination of statistics on women's access to digital devices and services reveals that 85% of them possess cellphone access, while 61.7% have internet access on their mobile phones. Their primary method of accessing the internet is via cellphone data. Mobile data charges are mostly dependent on mobile recharge retailers. Furthermore, a significant proportion of individuals (63.3%) actively engage in digital social communities, particularly on platforms such as WhatsApp. When it comes to internet services, the majority of individuals (61.7%) rely on mobile phones, while 36.7% depend on other sources. Individuals without internet connectivity on their mobile phones mostly rely on internet cafes or service centers for digital services.

(D) Findings based on Awareness and use of Digital payment mode

The significance of digital payment apps and wallets is growing steadily due to the proliferation of e-commerce, online shopping, and service platforms across numerous organizations. They provide secure, efficient, and convenient payment methods that are easily accessible to clients. An examination of data about the knowledge and utilization of digital payment applications and devices reveals that, exceptfor debit cards and UPI transactions, indigenous women exhibit little awareness and use of digital payment apps. While 83.3% of the individuals surveyed are knowledgeable about debit cards, just 36% use them primarily for withdrawing funds from their accounts. Among the responders who are knowledgeable about credit, just a mere 3.44% are using it for diverse purposes. The level of knowledge among rural women about Internet banking, mobile banking, and WhatsApp Money is very low, with just 16.66%, 15%, and 3.33% respectively being aware of these services. Furthermore, none of these devices are being used by rural women for conducting transactions. The combination of poor educational and financial status, together with the accompanying heavy reliance on males and the low position of women within families, leads to a lack of understanding and use of digital payment applications among women. The absence of economic, societal, and political empowerment among women poses a risk to the digital inclusion of rural women in other regions.

(E) Findings based on Problems of Using Digital Devices/services

The primary obstacles to digital inclusion for marginalized individuals, particularly rural women, are their limited digital literacy and subsequent lack of understanding and use of digital technologies. There are a lot of reasons why women don't know much about or use internet tools and services. The primary barrier hindering digital inclusion, as indicated by the majority of respondents (76.6%), is the lack of positive attitude and support from male family members towards women's knowledge and usage of digital devices.Furthermore, they expressed the view that male individuals who own digital gadgets refrain from sharing them with female individuals. Furthermore, the primary challenges faced by rural women in utilizing digital technology include inadequate access to quality education and language barriers (56.6%), insufficient digital infrastructure (61.6%), concerns regarding online safety (63.3%), inadequate proficiency and training in utilizing digital technology (33.3%), and limited awareness (46.6%).

(F) Findings based on Government Programs for Financial Inclusion

The impact of financial inclusion initiatives like as Pradhan Mantri Jan Dhan Yojana (PMJDY), Pradhan Mantri Jivan Jyoti Bima Yojana (PMJJBY), Pradhan Mantri Suraksha Bima Yojana (PMSBY), and Atal Pension Yojana (APY) on women living in urban slums in the Thanjavur District. The findings demonstrate that the PMJDY program has achieved significant success, particularly among women living in slums, and has a favourable impact on the social, political, and economic aspects of women's empowerment. This study adds to the current body of research by furthering the discussion on women living in urban slums and highlights the significant need for the establishment of a formal financial system to improve the extent of financial inclusion.

(G) Findings based on classification Accuracy

One usual way to judge how well a classification model works is to look at the results and see how accurate they are. The accuracy metric offers a clear and precise assessment of the model's ability to accurately predict class labels about the total number of predictions. In this case study, the SVM classifier is used for classification purposes. The algorithm properly detects the effect of digitalization on rural women with a rate of 96.64% in both training and testing. The accuracy and recall values for the model are 98.96% and 94.11% respectively. The forecast is derived from the four hypotheses that were established during the data pre-processing stage. The findings obtained are shown in Figures 7 and 8.

Figure – 7 *Performance Accuracy in Training and Testing*

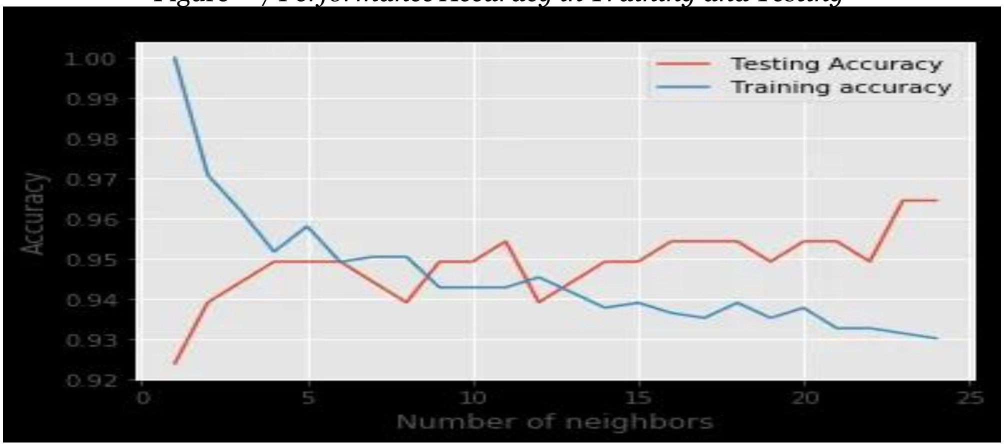


Figure – 8 *Performance Analysis of Proposed Method*

```
Scores
Accuracy --> 0.9644670050761421
Precison --> 0.9896907216494846
Recall --> 0.9411764705882353
F1 --> 0.964824120603015
MCC --> 0.9301703145220586
              precision    recall  f1-score   support

           0       0.94      0.99      0.96        95
           1       0.99      0.94      0.96       102

   micro avg       0.96      0.96      0.96       197
   macro avg       0.96      0.97      0.96       197
weighted avg       0.97      0.96      0.96       197
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Conclusion and Future Work

Digital finance has significantly facilitated the promotion of financial inclusion for women residing in rural regions, who have historically encountered obstacles in obtaining conventional banking services. The advent

of mobile banking, digital wallets, and other financial technology has empowered women to engage in transactions, accumulate savings, and get loans without the need for physical bank branches.
Digital finance platforms have enabled convenient access to loans and cash for female entrepreneurs in remote regions. Women may achieve economic autonomy by using mobile-based lending and microfinance applications to get loans for small-scale enterprises, agricultural projects, and other endeavours that generate revenue.
The primary obstacles to the digital inclusion of rural people and marginalized populations include the absence of digital infrastructure, particularly high-speed and consistent internet access, limited smartphone capacity and coverage, and a lack of proficiency in handling digital technology. Owing to the limited digital literacy among individuals residing in rural regions, particularly tribal communities, there is a lack of awareness and information about the use of digital devices and services to enhance their quality of life.The issue is far more severe for marginalized women. The research on the knowledge and use of digital technologies and services among women in the Thanjavur area provides insights into the level of women's participation in digital inclusion. An effective solution to this problem may be achieved by the implementation of a digital awareness campaign and the provision of targeted and cost-effective digital infrastructure assistance by the government. To address this problem, it is necessary to implement a focused digital awareness campaign led by authorities, which involves educational institutions, health centers, the agricultural department, and other relevant stakeholders.

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