Review Article

Machine Learning Applications in Suicide Prediction and Prevention: A Narrative Review

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Abstract

Background: Suicide is a complex and preventable public health issue where traditional statistical techniques have shown limited effectiveness in predicting future suicide deaths. Machine learning offers promising approaches to identify complex patterns and improve prediction accuracy. **Methods:** This narrative review examined the application of machine learning in suicide prediction by searching academic databases (PubMed, CINAHL Plus, IEEE Xplore) using MeSH terms 'Machine Learning' and 'Suicide.' English-language articles published within the last five years focusing on suicide, suicide deaths, and prevention were included. The final selection comprised 18 articles after removing duplicates. **Results:** Key risk factors identified included mental health conditions (particularly depression), socioeconomic factors (unemployment and financial difficulties), family-related issues, and demographic characteristics (age, gender). Various machine learning approaches demonstrated effectiveness in predicting suicide risk. K-Nearest Neighbors and ensemble models (combining Random Forest and XGBoost) showed particularly strong performance. Time series models like ARIMA variants excelled at temporal predictions, while ensemble methods demonstrated versatility with multiple data sources. **Conclusion:** Machine learning techniques offer substantial improvements over traditional approaches for suicide prediction, with model selection dependent on data availability, geographical scale, and temporal requirements. Ensemble methods perform best with multiple data sources, while time series models excel with temporal data.

Keywords: Machine Learning, Suicide, Prediction, Narrative Review, Prevention

Introduction

Machine learning has great potential to contribute to the field of public health. In recent times, there has been a growing interest in incorporating machine learning into suicide studies as a response to the lack of effectiveness of traditional statistical techniques in generating practical predictions of future suicide deaths (Bi et al., 2019; McHugh and Large, 2020). Suicide is considered a complex and preventable public health issue, but the appropriate identification and classification of people who are at risk of suicide are paramount to reducing the rate of suicidal deaths (Kabir et al, 2024; Bernert et al., 2020; Nordin et al., 2022).

Machine learning, a subfield of AI, emerged in the latter 20th century and is tied to computer science and statistics. Early programs in the 1950s played games like chess. Samuel's 1959 checkers program learned from mistakes and improved. Since then, machine learning has grown, improving knowledge and performance with experience. Machines can now autonomously recognise patterns and derive complex insights from data, evolving with new information(Linthicum et al., 2019). Machine learning techniques offer a more automated approach, employing algorithms to identify patterns and predict suicidal ideation based on large datasets. These methods can analyse diverse data sources, including electronic health records, social media posts, and text messages (Ji et al., 2021). Specific machine learning techniques include natural language processing to analyse text and other algorithms like support vector machines, and the deep learning model provides a comprehensive overview of these methods(Ji et al., 2021). The complexity of suicide and self-injurious behaviours has made it challenging to develop reliable predictive models using traditional statistical methods. To overcome these challenges, researchers have turned to machine learning techniques, which can identify complex, nonlinear patterns in data that may be missed by traditional approaches(Nordin et al., 2022). As the field of suicide research continues to evolve, the integration of machine learning techniques holds the promise of enhancing our understanding of this complex phenomenon and informing more effective prevention strategies (Schafer et al., 2021). Suicide risk assessment scales lack precision, but machine learning offers promise in prediction and prevention(Kirtley et al., 2022). Although, a minimal number of studies are conducted using social media data to predict suicide deaths with bias and lack of context issues(Kirtley et al., 2022). This narrative review evaluates the effectiveness of various machine learning approaches in suicide prediction and to identify the most appropriate models based on different contexts, data availability, and population characteristics.

Methods

A narrative review was conducted as it is a valuable tool to explore and evaluate existing literature on a topic comprehensively. Additionally, it presents an overview of current knowledge while conducting subjective analysis and critical evaluation of available literature. Simultaneously, narrative review helps identify gaps in under-researched areas while offering fresh perspectives on well-established topics(Sukhera, 2022). Academic databases such as – Pubmed, CINAHL Plus and IEEE Explore were searched using MeSH terms ‘Machine Learning’ and ‘Suicide’. Inclusion criteria such as English language, published within the last five years, only focus on suicide, suicidal deaths and suicide prevention, empirical research, conference papers and review articles were used to select the articles. Three databases were systematically searched: PubMed (biomedical and life sciences), CINAHL Plus (nursing and allied health), and IEEE Xplore (computer science and engineering). This combination ensures comprehensive coverage across three interdisciplinary domains: clinical understanding of suicide epidemiology, health services implementation, and technical machine learning methodology (Kabir et al, 2023; Kabir et al, 2024). Machine learning is rapidly evolving. A 5-year window (2019-2024) captures recent algorithmic developments (transformer models, advanced ensemble methods) while excluding outdated approaches (Kabir et al, 2025).

The article selection process followed a systematic approach across three significant databases: PubMed, CINAHL Plus, and IEEE Xplore. The initial search employed specific terms, including 'Machine Learning' AND 'Suicide' and 'Machine Learning' AND 'Suicide Deaths'. This search yielded varying results across databases: PubMed returned 649 hits, CINAHL Plus produced 162 results, and IEEE Xplore generated 35 matches. After the initial database search, all abstracts were thoroughly reviewed and assessed for eligibility criteria. This evaluation process identified 53 relevant articles from the database searches, while an additional six articles were discovered through manual searching methods. In the final step, duplicate articles were carefully removed from the selection pool. After this refinement, the final selection comprised 18 articles for a comprehensive review. The findings are presented in a thematic pattern.

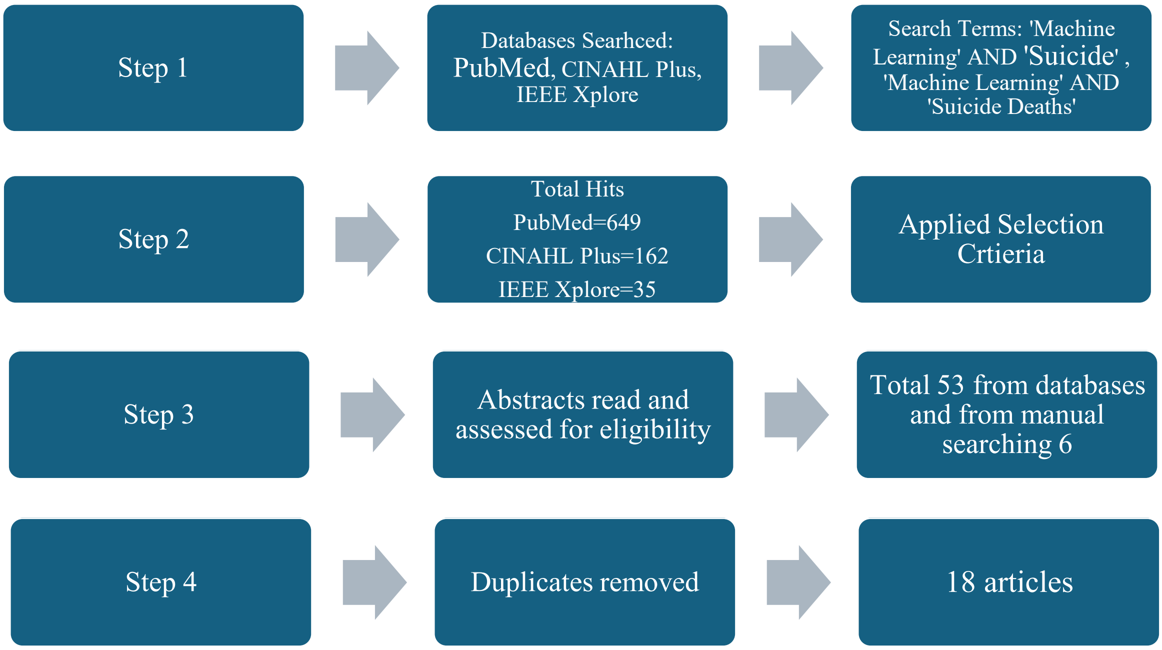
Results

Table 1 presents key research on suicide. The table synthesizes key information, including study aims, data sources, methodological approaches, main findings, and limitations. A notable pattern emerges across these studies: while earlier research (2020-2021) primarily focused on demographic risk factors and basic prediction models, more recent studies (2023-2024) have evolved toward sophisticated ensemble methods and multimodal analyses. The studies consistently highlight the value of machine learning in suicide prediction, with K-Nearest Neighbors and ensemble models showing powerful performance. However, common limitations persist across studies, including data quality issues, limited timeframes, and the challenge of accounting for complex socioeconomic factors.

Theme 1 Risk Factors: Multiple studies identified consistent risk factors across different populations. Mental health conditions, particularly depression, emerged as a primary risk factor (Singh et al 2024; Roy et al, 2021; Swain et al, 2021). Socioeconomic factors played a crucial role, with unemployment and financial difficulties significant predictors (Matsumoto et al., 2023; McIntyre and Lee, 2020; Okada et al., 2024). Family-related issues, including domestic violence and relationship problems, were also very significant (Anjali, 2024; Gupta, Jain and Rout, 2024). Age and gender were critical demographic factors, indicating higher rates among those under 35, and males showed 2-4 times higher rates than females (Biplob et al., 2023; Nikam et al., 2023). Previous suicide attempts and substance abuse were identified as strong predictors (Gradus et al., 2020). Kumar et al. (2022) emphasised geographical variations, noting higher rates in western US states (Kumar et al., 2022). For elderly populations, (He et al., 2021) identified specific risk factors, including isolation, being widowed, and physical illnesses. During the COVID-19 pandemic, Okada et al. (2024) found that pandemic-related stressors particularly impacted vulnerable populations (He et al., 2021). In the agricultural sector, Rajani et al.

(2024) highlighted specific factors like excessive debt loads and crop failure as major contributors to farmer suicides (Rajani et al., 2024).

Figure 1: Article Selection Process



Theme 2 Models used and best performing model: The studies employed diverse statistical and machine-learning approaches for suicide prediction, each showing distinct strengths in different contexts. Time series models, particularly ARIMA variants, demonstrated strong performance for temporal predictions. Basic ARIMA models (Roy et al, 2021; Swain et al, 2021) showed effectiveness with historical data, while Seasonal ARIMA (sARIMA) excelled at capturing seasonal patterns and pandemic-related changes (Okada et al, 2024). Kandula et al. (2023) significantly improved ARIMA performance by incorporating external data like crisis hotline calls and Google Health Trends (Kandula et al., 2023). For multivariate analysis, Vector Autoregressive (VAR) and Vector Autoregressive Moving Average (VARMA) models showed superior performance when handling multiple interconnected variables (Anjali, 2024).

Machine learning approaches demonstrated remarkable versatility. Ensemble methods, particularly the combination of Random Forest and XGBoost (Singh et al 2024), achieved impressive results with an AUC-ROC score of 0.83 and an F1-score of 0.76, showing strength in handling multiple data types while maintaining a balance between precision and recall. Random Forest alone showed gender-specific effectiveness, with AUC scores of 0.80 for men and 0.88 for women (Gradus et al., 2020), particularly excelling at identifying high-risk individuals in the top 5% of predicted risk cases. K-Nearest Neighbors demonstrated strong performance (86.09% accuracy) in specific contexts like farmer suicide prediction (Rajani et al., 2024), while XGBoost achieved remarkable accuracy (R^2 value of 0.98) at county-level predictions (Kumar et al., 2022).

More recent studies have shown promising results with specialized applications. The Random Forest Classifier achieved 99% test accuracy across different risk categories (Biplob et al, 2023), showing strength in continent-based analysis and multi-class risk categorization. Decision Tree Classification (CART) demonstrated high effectiveness (90.476% accuracy) in questionnaire-based individual risk assessment (Nikam et al, 2023).

Table 1: Characteristics of included studies

Reference	Aim	Data and Sample	Machine Learning Approach used	Key findings	Limitations
Gradus et al. (2020)	To examine sex-specific risk profiles for suicide deaths using machine learning	Population-based data from Denmark (n=14103)	Classification tree (CART) and Random Forest Model	Sex-specific differences were noted in the risk of suicide	No data is available on pre-suicide predictors like interpersonal stress.
Gupta et al (2024)	The study aims to predict suicide rates in India on a state-wide basis by utilising various machine learning algorithms.	Data from Kaggle on different states of India	Regression, K Nearest Neighbours, Lasso and Random Forest and Bayesian Ridge	Predictions based on longitudinal data are more accurate than those based on cross-sectional data.	The research relies on existing datasets, which may be incomplete or lack detailed information on various factors.
Singh et al (2024)	To critically analyse AI-powered prediction models for suicide risk assessment, examining their challenges, opportunities, and implementation considerations.	A multimodal dataset of 5,000 individuals (500 suicide-related cases and 4,500 control cases) combining electronic health records (EHR), psychometric results, and social media activity.	Logistic Regression Random Forest XGBoost LSTM (Long Short-Term Memory) CNN (Convolutional Neural Network) Ensemble model (combining Random Forest and XGBoost)	The ensemble model performs the best.	Small sample size
Rajani et al (2024)	To predict and analyse farmer suicides in India using machine learning algorithms	Kaggle dataset spanning 2001 to 2012	Random Forest Decision Tree Naive Bayes Classifier Gradient Boosting Logistic Regression K-Nearest Neighbors (KNN)	KNN performed best	The dataset is limited to 2001-2012, potentially missing more recent trends
Nikam et al (2023)	To propose an automated system for predicting suicide rates across different states in India	A dataset from Kaggle titled "Suicide in India."	Linear Regression Decision Trees • ID3 (Iterative Dichotomiser 3) • CART (Classification and Regression Trees)	Linear Regression achieved 85.98% accuracy. Maharashtra had the highest suicide rates	Limited to Indian data only, not worldwide
Biplob et al (2023)	To predict suicide rates across different continents using	Dataset from Kaggle n=27,820	Stochastic Gradient Descent	KNNC achieve the highest training accuracy	Limited to the 1985-2016 timeframe

	machine learning approaches		Classifier (SGDC) Random Forest Classifier (RFC) Gaussian Naive Bayes Classifier (GNBC) K-Neighbors Classifier (KNNC) Logistic Regression Classifier (LRC) Linear Support Vector Classifier (LSVC)	Men have higher suicide rates than women age The age group 35-54 has the highest number of suicide cases	
Kumar et al (2022)	To analyse suicide trends across US counties, develop a machine learning-based county-level suicide prediction model, and create a Suicide Vulnerability Index (SVI) to identify high-risk regions.	Data from 3,140 US counties over 10 years (2010-2019)	eXtreme Gradient Boosting (XGBoost) for prediction SHapley Additive exPlanations (SHAP) for feature importance analysis	25% of counties showed at least a 10% increase in suicides from 2010-2019 Western US consistently showed higher suicide rates	Some suicides may be misclassified or unreported Unable to capture variations within counties
He et al (2021)	To examine time trends of suicide mortality for people aged 70+ years by sex, age, and location from 1990-2017	1. Global Burden of Disease (GBD) study 2017 data: • Age-standardised suicide mortality data from 183 countries (1990-2017) • Complete bibliographic records from the Web of Science database for 158 countries 2. Sample size: • 118,813 suicide deaths in	Hierarchical Clustering Restricted Cubic Spline ARIMA (Autoregressive Integrated Moving Average)	In 2017, the global suicide mortality rate for the 70+ age group was 27.5 per 100,000	Data quality issues, especially in low-income countries without robust, vital registration systems

		people aged 70+ in 2017 • The analysis covered 195 countries and territories • 21 GBD regions			
Lange et al (2024)	To estimate the impact of implementing national level means restriction policies (firearm and pesticide restrictions) on suicide mortality rates in the Region of the Americas.	▪ Data from WHO Global Health Estimates database (2000-2019) ▪ The sample included 33 countries from the Region of the Americas	▪ Ecological modelling study using panel data analysis	▪ By 2030, male suicide rate would be 20.5% lower ▪ Female suicide rate would be 11.1% lower ▪ Estimated 113,580 deaths could be avoided over 10 years	▪ Potential bias in suicide statistics across countries ▪ Differences in classification and registration methods
Roy et al (2021)	To examine the trend and structural breakpoints of suicide in India for 53 years (1967-2019)	▪ Secondary data from the National Crime Record Bureau (NCRB), India ▪ 53 years of suicide data from 1967-2019	▪ ARIMA (Autoregressive Integrated Moving Average) modelling ▪ Structural breakpoint analysis using F-tests ▪ Stationarity testing using: ▪ Augmented Dickey-Fuller test ▪ ACF and PACF plots	ARIMA(1,2,2) was identified as the best model for forecasting male, female and total suicide numbers	The study relies only on officially reported cases, and potential underreporting was not accounted for.
Matsumoto (2020)	To analyse the relationship between unemployment rates and suicide mortality rates in Japan from 2009-2022, particularly examining how different types and durations of unemployment impact suicide rates across	▪ Monthly suicide numbers by gender and age groups from Basic Data on Suicide in the Region (BDSR) ▪ Population data from the Regional	▪ Interrupted Time Series Analysis (ITSA) with robust standard error ▪ Joinpoint Regression Analysis (JPRA)	▪ Dismissal-related unemployment strongly impacted suicide rates among working-age populations ▪ Short-term unemployment (3 months) affected female suicide rates more immediately	Cannot comprehensively analyse complex interactions among multiple suicide risk factors

	gender and age groups	Statistics System ▪ Monthly unemployment rates by reason from Labor Force Survey (LFS)		▪ Long-term unemployment (12+ months) had more substantial effects on male suicide rates	
McIntyre and Lee (2020)	To project the number of excess suicides in Canada due to COVID-19-related unemployment increases.	▪ Annual suicide mortality data (2000-2018) from Statistics Canada's Vital Statistics - Death Database ▪ Annual unemployment data (2000-2019) from Labour Force Survey ▪ Suicide rates coded using ICD-10 codes for intentional self-harm	Time-trend regression models	• Projected excess suicides for 2020-2021: • Moderate scenario: 418 excess deaths (+5.5% annually) • Extreme scenario: 2,114 excess deaths (+27.7% annually) • Suicide rates are projected to increase from 10.9 to 11.6-14.0 per 100,000 in 2020	A single variable (unemployment) cannot fully predict suicide risk
Anjali 2024	To explore cause-specific suicide prevention strategies in India using multivariate time series analysis to model and forecast suicide patterns.	▪ 21 years of annual time series data (2001-2021) from the National Crime Records Bureau (NCRB)	▪ Univariate ARIMA ▪ Multivariate VAR (1) ▪ Multivariate VARMA (1,1) ▪ Used Python-3 with techniques including: ▪ Augmented Dickey-Fuller test for stationarity ▪ Granger causality test ▪ Johansen cointegration test	VARMA (1,1) outperformed other models with the lowest MAE, RMSE, and MAPE values	▪ Limited to national statistics without regional variations ▪ Demographic details like gender and age are not considered
Chaban et al (2023)	To create statistical models for	▪ Monthly suicide mortality	▪ Autocorrelation analysis and	▪ Identified clear seasonal patterns with peaks in	Could not build forecasts for some

	forecasting seasonal suicide rates across different regions of Ukraine and build predictions for suicide mortality trends	data from 2005-2021 from the State Statistics Service of Ukraine	correlograms to identify periodicity ▪ Time series modelling using: ▪ Interrupted time-series analysis (ITSA) ▪ Join point regression analysis (JPRA) ▪ Exponential smoothing with seasonal component ▪ Ljung-Box statistics for model validation	spring months and January ▪ A decrease in suicides typically occurs in autumn ▪ Models predicted increased suicide rates for spring 2022	regions due to data quality issues
Okada et al (2023)	To review trends in suicide mortality rates in Japan before and during the COVID-19 pandemic, analyse underlying causes, and evaluate the effectiveness of suicide prevention strategies.	▪ Suicide mortality data from 2009-2023 from Japanese government databases	▪ Interrupted time-series analysis (ITSA) ▪ join point regression analysis (JPRA) ▪ Vector autoregressive (VAR) modelling ▪ Hierarchical linear models (HLMs) ▪ Granger causality testing ▪ Impulse response analysis	Suicides increased in Japan starting in 2020, the first country to show a pandemic-related increase	Cannot entirely separate pandemic effects from other social factors
Swain et al (2021)	To analyse suicide trends in India over 50 years (1969-2018) and forecast suicide rates for the next decade using time series modelling.	▪ Source: National Crime Record Bureau (NCRB) reports, India ▪ Period: 1969-2018 (50 years) ▪ Type: Longitudinal time series data	▪ ARIMA (Auto-Regressive Integrated Moving Average) modelling ▪ Best fit model: ARIMA (4,1,0) selected based on AIC, BIC, and AICc values	▪ Consistent rise in suicide rates over five decades ▪ Male suicide victims (66.2%) nearly double compared to females (33.8%)	Used secondary data (NCRB records), which may have under-reporting

			▪ Model validation: Box-Pierce test and residual analysis		
Kandula et al (2023)	To evaluate the feasibility of generating monthly 6-month ahead forecasts of suicide mortality across US states using crisis hotline calls and Google search data to supplement traditional surveillance data	▪ National Vital Statistics System (NVSS) suicide mortality data (2007-2020)	Autoregressive Integrated Moving Average (ARIMA)	▪ All models improved over baseline random walk ▪ Proxy data (calls/searches) improved forecast quality	Socioeconomic/clinical predictors not included
Biddle et al (2019)	▪ To analyse patterns and trends in Australian suicide mortality from 2007-2018 ▪ To develop and test forecasting models for predicting future suicide rates	▪ Monthly suicide deaths in Australia from 2007-2018 ▪ Data sourced from the National Mortality Database via the Australian Institute of Health and Welfare	Tested five forecasting models: ▪ Exponential Smoothing State Space (ETS) Model ▪ Autoregressive Integrated Moving Average (ARIMA) Model ▪ TBATS Model (Exponential smoothing with Box-Cox transformation) ▪ STL Model (Seasonal decomposition using Loess) ▪ Neural Network Autoregression Model	▪ Increasing suicide rate over the 2007-2018 period ▪ Steady rates until 2010, increased 2010-2015, fluctuated thereafter ▪ Male rates are approximately three times higher than female rates	Cannot adjust for changing age structure of population

Discussion

Model performance patterns revealed important contextual considerations. For large datasets with multiple variables, ensemble methods and VARMA models typically outperformed more straightforward approaches. Simpler models like basic ARIMA and KNN proved more reliable in scenarios with limited data. Geographic scale also influenced model effectiveness: time series models excelled at national-level predictions, while machine learning approaches like KNN and XGBoost showed stronger regional and local-level analysis performance. Temporal considerations were equally important - augmented ARIMA models and machine learning approaches with real-time data inputs performed better for short-term predictions. In contrast, basic ARIMA and VARMA models showed reliability in long-term forecasting.

These findings suggest several key insights: (1) Model selection should be guided by data availability and context-ensemble methods for multiple data sources, time series models for temporal predictions with limited variables, and specialized approaches like KNN or CART for specific demographic groups; (2) Performance can be optimized by incorporating multiple data sources when available and considering seasonal patterns in temporal analysis; (3) The balance between model complexity and data availability is crucial for reliable predictions; and (4) Geographic scale, data availability, temporal requirements, and population characteristics significantly impact model performance and should guide model selection and implementation strategies.

Conclusion

Machine learning approaches showed remarkable versatility and improved predictive performance compared to traditional statistical methods. Ensemble methods, particularly combinations of Random Forest and XGBoost, achieved impressive results with high AUC-ROC scores and balanced precision and recall metrics. K-Nearest Neighbors demonstrated strong performance in specific contexts like farmer suicide prediction. Time series models, especially ARIMA variants, excelled at temporal predictions, with performance further enhanced when incorporating external data sources.

Based on these findings, several recommendations emerge for researchers and public health practitioners. First, model selection should be guided by data availability and context—ensemble methods for multiple data sources, time series models for temporal predictions with limited variables, and specialized approaches for specific demographic groups. Second, incorporating multiple data streams, including non-traditional sources like crisis hotline calls and social media data, can significantly enhance prediction accuracy. Third, considering geographical and temporal dimensions is crucial, as different models show varying effectiveness at national, regional, and local levels.

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