IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received September 7, 2021, accepted September 17, 2021, date of publication September 29, 2021,
date of current version October 7, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3116205

Development of Risk Assessment Framework for First Time Offenders Using Ensemble Learning

AMAN SINGH AND SUBRAJEET MOHAPATRA
Department of Computer Science and Engineering, Birla Institute of Technology, Mesra (BIT Mesra), Ranchi 835215, India
Corresponding author: Aman Singh (amansingh281291@gmail.com)

ABSTRACT Recidivism is generally considered as a deficiency disease in which offenders recommend a crime or repeat an offence. Empirically committing the first crime at a very young age leads to a much higher rebound rate and the continuation of similar offensive behavior. Accordingly, prioritization must be given for the early assessment of recidivism behavior in first-time offender by law enforcing agencies. Different prison studies suggest that recidivism can be curtailed by early behavioral risk assessment in first-time offenders. Ideally, a psychologist conducts a manual risk assessment using standard psychological assessment tools, which has long been regarded as a standard method for recidivism risk assessment. However, such behavioral examination procedures are usually sluggish and constrained by subjective perceptions. Consequently, this study aims to develop a machine learning-based quantitative risk assessment tool for the recidivism behavioral gradation of first-time offenders. Quantitative gradation and prediction of future recidivism behavior in such offenders are achieved using an ensemble learning model and an advanced machine-learning approach. For the available behavioral data collected from multiple prison locations, simulations were performed, and the experimental results were obtained. It is ascertained that, the proposed three-member and five-member ensemble classifier models lead to 85.47% and 87.72% accuracy respectively in comparison to other standard individual classifiers.

INDEX TERMS Recidivism, first time offenders, predicting criminal recidivism, quantitative psychology, ensemble learning model.

I. INTRODUCTION

Crime is defined as a deliberate testimony or eviction to disobey criminal law that is carried out without any barrier or defence and is sanctioned by the government as a lawful offence or offence. Whereas, criminal behavior can be defined as any visible or hidden violation of law that is punishable upon conviction. The following are some broad categories of crimes under the Indian Penal Code:

- *Crimes Against Body:* Murder, Kidnapping & Abduction
- *Crimes Against Property:* Theft, Dacoity, Robbery, and Burglary
- *Crimes Against Public Law:* Torching and Anarchy
- *Crimes Against Women:* Rape, Dowry death, Domestic violence
- *Crimes Against Children and Adolescents:* Sexual assault, Kidnapping of child
- *Economic Crimes:* Tax evasion, Bribery, Money Laundering

In this respect, criminology or crime science is the scientific study of crime and criminals and their motivations for engaging in criminal behavior [1]. Crime science is an interdisciplinary area of research that focuses on the logical investigation of felony and criminal conduct, including their signs, causes, legal angles, and control. Criminals' wills, thoughts, intentions, reactions, and everything else involved in the conduct of criminal behavior. It is founded on various disciplines such as sociology, anthropology, psychology, psychiatry, philosophy, and generic medication. The most important motivation for criminology is to identify psychological factors that underpin criminal behavior [2].

There are two types of criminological research studies: qualitative and quantitative. Qualitative research includes studies that collects and analyze crime data in order to better understand crime instances and criminals independent of their relationship to individual cases [3]. Quantitative criminology deals with study of criminal behavior, crime

The associate editor coordinating the review of this manuscript and approving it for publication was Yiming Tang.

prediction, and computer aided interpretation of crime data for crime prevention of crime [4]. Various statistical and predictive models interpreting large-scale data sources in crime and quantitative analysis of criminal behavior have been implemented as crime data and crime rates have grown [5]. Such quantitative methods provide many ways to interpret crime data, which is beneficial to many aspects of society. The use of quantitative methods assists criminologists and law enforcement agencies in the field of crime prevention and criminal rehabilitation.

As per empirical studies, the quantitative study of criminal behavior is exceptionally essential in criminal rehabilitation and crime prevention among different types of crime data analysis. In recent years, development of quantitative methods for the analyzing criminal behavior has become extremely important for the routine monitoring of personality imbalances, impassivity and anti-social syndrome among first-time offenders (FTOs). Some of the identified risk factors that augment towards the recurrence of crime after the first conviction among FTOs are presented below.

- Demographic
- Socio-Economic
- Employment
- Literacy
- Vocational Skills
- Interpersonal skills

In addition, life-long study of offenders to identify the recurrence of crime in offenders is referred to as criminal recidivism. Studies related to criminal activity by age show that committing a crime at a younger age indicates a broader criminal career in offenders. Furthermore, research also shows that an individual with a lengthy criminal background committed his/her first crime at a young age [6]. First-time offenders on average have a higher probability of reconviction compared to those with extensive criminal records.

A first-time offender is someone who has been convicted for the first time in the criminal justice system. [7]. Moreover, recidivism, or committing a crime again, is a widespread phenomenon among first-time offenders. To minimize crime and preserve law and order, it is critical to detect recidivism activity among FTOs early and provide rehabilitation services. According to A. W. Macleod, recommending a crime or repeating an offence is a deficiency disorder that causes offenders to break the law or disobey the government regularly [8]. Recidivism in FTO has been linked to several individuals and environmental risk factors, as mentioned above. According to studies, poverty, illiteracy, drug abuse, anti-social personality disorder, intermittent explosive disorder, and a lack of family support are among the most common reasons for first-time offenders to recommend a crime or return to prison.

One of India's growing problems is the rise in criminal recidivism. According to the National Crime Records Bureau of India, the current crime rate in Jharkhand, a state in India is 1.4 percent of the total population, ranking it eighteenth in overall crime incidents. Researchers in criminology are particularly interested in the rising rate of recidivism among young offenders. Recidivism must be predicted early to provide individualized rehabilitation and ensure effective social integration. Furthermore, whether first-time offenders will recidivate or not, regular behavioral assessments are needed to reintegrate them into society. The use of machine learning based methods for routine criminal behavioral evaluation is a major step toward reducing crime in the society.

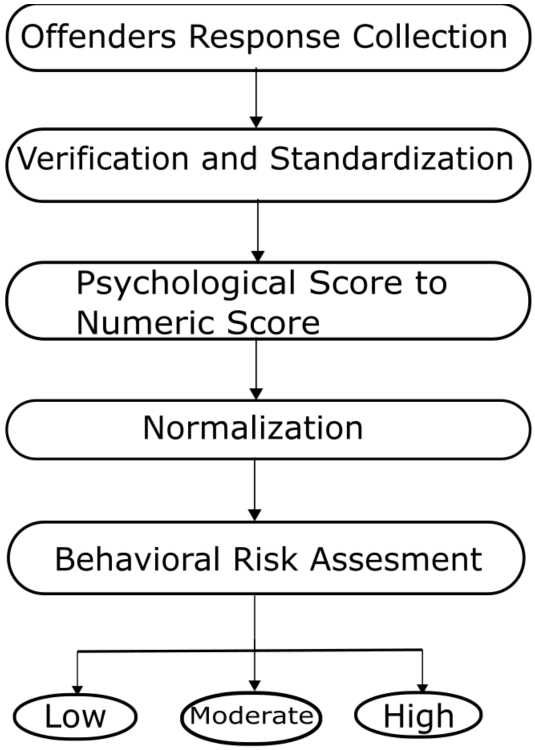

FIGURE 1. Workflow of the proposed system.

Consequently, the primary contribution of this study is the development of an ensemble of classifier models for assessing risk and predicting recidivism among first-time offenders. The proposed computational framework for risk evaluation and recidivism prediction is shown in Figure 1. The outline of this article is summarized as follows. Section II provides a detailed description of the other available literature on computational approaches to criminology. Section III describes the source of prison data, the survey questionnaire-based behavioral data collection process, and other approaches used in the proposed study. Details regarding application of ensemble of classifiers for recidivism risk assessment are outlined in Section III-F. Details regarding the performance evaluation and analysis is presented in Section IV. The experimental findings and discussion is presented in Section V. Finally, the conclusions are summarized in Section VI.

II. LITERATURE REVIEW

Computational criminology refers to the application of computer–assisted methods in various areas of criminology. It's a blend of disciplines where forensic psychologists, criminologists, and computer scientists collaborate to develop intelligent problem-solving methods in various criminology areas [9], [10]. Several researchers have focused on developing computational models for forensics, crime pattern identification, environmental criminology, and criminal justice systems in recent years. Specifically, a significant proportion of work has been conducted to identify crime pattern prediction and detection [11]–[14]. A significant number of studies have also been devoted to understanding the significance of environmental factors in criminality and developing cognitive models to simulate criminal behavior [15]–[18]. Moreover, few authors have addressed recidivism prediction and risk assessment [19]–[25] Additionally, few research articles are available on the application of machine learning to the criminal justice system (algorithmic justice), viz. automated determination of jail terms and parole sanctioning [26]–[29]. Hence, from the available literature on computational criminology, it is observed that most of the research done to date can be categorized into four groups:,

a. Crime Pattern Prediction and Detection
b. Cognitive Modeling approach for Criminal Behavior
c. Recidivism Prediction and Risk Assessment
d. Algorithmic Justice

It was observed that topics related to Crime Pattern Prediction, study of Cognitive Models for criminal Behavior and Algorithmic justice are directly/indirectly related to re-commitment of crime/ offence by offenders. The relationship between each categories has been tabulated below–

TABLE 1. Relationships between different categories of literature available in computational criminology.

Crime Pattern Prediction and Detection	Study of recidivism criminal behavior is essential for early prediction of recommitment of crime by offender.
Cognitive Modelling approach for Criminal Behavior	Research on different cognitive models essential for understanding individual recidivism criminal behavior especially in FTO's.
Algorithmic Justice	Detailed study of recidivism criminal behavior for FTO's and recidivists are highly desirable for deciding criminal judgement viz. parole outcome, sentencing and bail out.

Hence it was concluded that study of recidivism risk assessment is highly correlated to the above three categories. As a result, we include a thorough discussion of articles related to machine learning in predicting recidivism and risk evaluation among offenders in the current work.

A. RECIDIVISM PREDICTION AND RISK ASSESSMENT

Caulkins et al. [19] implemented both neural networks and traditional statistical models for the prediction of criminal recidivism. They showed that, despite their properties that may be useful for predicting recidivism, network models do not outperform other widely used datasets. Their findings indicated that, irrespective of the models or procedures used, the prediction attributes used have minimal knowledge representation content for characterizing recidivists.

Hilton et al. [20] discussed various actuarial and clinical methods for violence risk assessment. They found that actuarial tests are the most accurate way to measure the risk of aggression over time and allocate intervention resources in addition to therapeutic approaches.

Piquiro et al. [21] conducted a theoretical meta-analysis of the literature on violent re-offence, emphasizing various demographic risk attributes. According to their research findings, age, gender, and race were all linked to violent recidivism.

Fawn et al. [22] conducted a comparison study to assess the relative utility of three classification strategies in predicting inmate misconduct: classification and regression tree (CART), chi-squared automatic interaction detection (CHAID), and multi-layer perceptron neural network. To evaluate the four different models and risk factors derived from the importation framework on inmate adaptation, a group of inmates from state and federal prisons were considered. The predictive accuracy of the four models was evaluated and recorded using a multi-validation protocol and multiple assessment indicators, with overall accuracy ranging between 0.60 and 0.66.

Wijenayake et al. [23] introduced a decision-tree classifier based approach for predicting recidivism concerning domestic violence. They attempted to introduce and test various approaches for dealing with class imbalance and feature selection particularly for the prediction of recidivism among convicted domestic violence offenders.

Fang et al. [24] used a combination of combination of principal component analysis (PCA) and support vector machine (SVM) for the forecasting of criminal obsession among high-risk personnel based on reported behavioral data. They used PCA to reduce the dimensionality of behavioral data before predicting criminal tendencies using different SVM kernel functions.

Wang et al. [25] investigated different interpretable machine-learning models for accuracy, interpretability, and fairness in criminal recidivism prediction. For criminal recidivism prediction, various interpretable machine learning methods with various degrees of interpretability, ranging from scoring systems to decision trees to additive models, were simulated.

Based on our literature review, we identified the following issues that must be addressed:

i. A limited number of studies on recidivism risk assessment in FTOs.
ii. Independent risk factors, such as demographic and socio-economic factors, have only been considered to automatically characterize criminal behavior.

iii. None of the researchers considered using hybrid features to develop a machine learning-based model for recidivism risk assessment in FTOs.
iv. Non-utilization of ensemble machine learning model

In conclusion, while the above schemes are helpful for a number of computational criminology issues, they may not be suitable for predicting the risk of recidivism in first-time offenders. Furthermore, due to the significant variation in criminal behavior worldwide, additional regional variables must be identified. Thus, the key offerings of this research include the establishment of a machine learning-based model for recidivism risk assessment in first-time offenders.

III. DATA AND METHODS

The details of the behavioral data acquisition technique and the structure of the proposed method, as outlined in the following subsection, are described in this section.

A. STUDY SUBJECT SELECTION

Assessment of offenders behavioral traits may reveal the degree of delinquency in a person's personality, which is strongly linked to habitual recidivism. Therefore, in the current study, behavioral data were gathered from various prisons and special homes in the state of Jharkhand for the early prediction of recidivism in first-time offenders. Criminal behavioral assessment were conducted by prison counselors periodically over four months to maintain data integrity.

A total of 204 male prisoners were included in this experimental study based on strict guidelines for inclusion and exclusion. The participants' ages ranged from 18 to 30 years, with the majority falling below the poverty line. Each participant was interviewed using a behavioral questionnaire developed by a panel of clinical psychologists based on Structured professional judgement (SPJ) and Present status examination (PSE) standard globally followed [30]. The HCR-20 [31] risk assessment indicator for early recidivism prediction was included in the questionnaire, together with other clinical and non–clinical risk factors. Each behavioral trait considered here serves as a specific marker of delinquency in a participant's personality. To ensure data accuracy, all prisoners were interviewed over the course of four months by qualified prison counsellors who were psychology graduates, who asked the same questions to all of them. Additionally, to remove bias from the experiment each inmate's prison behavioral experience is also reviewed through feedback from the jail Superintendent and the concerned vocational teacher. A detailed summary of the distribution of offenders based on different risk factors is presented in Table 2.

B. BEHAVIORAL FEATURE MEASUREMENT

The proportion of delinquent behavioral traits present in the FTOs was used to determine the criteria for recidivism risk assessment. Since its inception, the HCR-20 [31] violent risk assessment scale has been a required structured method for assessing the risk of violence in criminals. However, observational studies have shown that using only HCR-20 to predict recidivism among first-time offenders without using regional factors is insufficient. As a result in this study, HCR-20 along with individual, socio-demographic, family, and cumulative prison behavior factors, has been used to develop of ensemble machine learning model for assessing risk and predicting recidivism among first-time offenders. Table 3 and 4 summarizes both clinical and non-clinical risk factors used in this study for quantitative evaluation of recidivism among FTOs, and are also practised by the majority of psychologists across the globe.

TABLE 2. Summarized categorization of offenders based on different criterion.

Classification Criteria	Types	No. of Participants
Employment	Employed	57(%)
	Unemployed	47(%)
Personality & Current Prison Behavior*	Anti Social Personality Disorder (ASPD)	159
	Violent Attitude	167
	Depression	120
	Reoffending Behavior	132
Nature of Crime	Murder	13 %
	Sexual Offence	47 %
	Burglary and others	40 %

*Observed behavioral overlapping

TABLE 3. Non-clinical risk factors for recidivism risk assessment in first time offenders.

Risk Factors		Measured Variables/ Attributes	Scores	Assessment Tools
Socio Demographic	Marital Status	Unmarried	1	Semi-structure performa prepared by clinical psychologist
		Married	0	
		Divorced	2	
	Educational	Illiterate	2	
		High school	1	
		Intermediate	0	
		Graduation and above	0	
	Occupation	Student	1	
		Unemployed	2	
		Farmer	0	
		Service	0	
		Business	1	
	Age	Young Adults	1	
		Adults	0	
Family/ Parental/Peer		Parental Conflict	2	Semi-structure Performa prepared by clinical psychologist
		Single divorced	1	
		Dysfunctional family	2	
		Parental Criminal Activity Involvement	2	
		Family Financial Condition	2	
		Peer Association(Criminal Connection)	2	

TABLE 4. Clinical risk factors for recidivism risk assessment in first time offenders.

Risk Factors		Measured Variables/ Attributes	Scores	Assessment Tools
Individual		Personality	1	Semi-structure Performa prepared by clinical psychologist
		Self control	Low/Moderate/High	
		Substance Abuse	0/1/2	
		Loneliness / Depression	0/1	
		Emotional Stability	Stable/ Unstable	
		Intellectual Level	Low/ High	
Delinquent Behavior	Historical (H)	10 domains (Violence Types, Traumatic Experiences, Major Mental Disorder etc.)	Minimum–20 Maximum–40 0–mild 1–moderate 2–high	HCR-20
	Clinical (C)	05 domains (Negative Attitudes, Unresponsive to treatment etc.)		
	Risk Management (R)	05 domains (Stress, Depression Lack of personal Support etc.)		
Cumulative Prison Behavioral Assessment		Present mental status	Poor/ Average/ Good	Semi-structure Performa prepared by clinical psychologist
		Psychomotor activity	low/moderate/ high	
		Orientation	Oriented	
		Participation	Yes/ No	
		Speech and Voice	low/moderate/high	

C. FEATURE REPRESENTATION

The created dataset consists of 220 rows and 57 columns, where each row represents an individual inmate, and the corresponding column reflects the evaluated behavioral traits

TABLE 5. Summarized feature table.

Factors	Significant features (p<0.05)
Personality factors	Social attitude*(F8 to F13) Unemployment and Education*(F1 to F3) Self description and Greedy*(F14, F15) Physical violence* (F5, F6) Offence and Guilty (F28, F29, F32)
Family and Parental Factors	Parent crime activity* (F16, F36) Family property disputes* (F17,F18,F37) Family Financial status* (F19, F20)
Environmental Factors	Friends past crimes* (F22, to F24) Friend criminal activity* (F25, F26)
Sentencing Duration	Parent/ family prison visit* (F27, F41) Incarceration length* (F31, F33) Lack of Vocational Training* (F42, F43) Psychological well being* (F44, F45)
HCR-20(Historical, Clinical and Risk Management) Historical Items	H1- Previous violence* (F46) H2- Other anti social behavior* (F47) H3* to H6*(F48 to F51) H7* and H8* - Psychopathy and Personality Disorder* (F52, F53) H9* and H10* - Violent attitudes* and Supervision Failure (F54, F55)
Clinical Items	C1* to C5* (F56, F57, F58, F59, F60)
Risk Items	R1* to R5* (F61, F62, F63, F64, F65)

*Significant features based on ANOVA

TABLE 6. Summarized feature table.

Factors	Insignificant features (p>0.05)
Personality, Socio-economic and Demographic Factors	Parents education* (F8) Parent illness* (F11) Family structure* (F25) Family decisions* (F34) Birth position* (F38) Sibling relations* (F39) Friends charity* (F43) Traumatic violence* (F44)

* Insignificant features based on ANOVA

obtained via a personalized interview. Moreover, based on feedback from an experienced group of qualified psychologists from the Central Institute of Psychiatry, Ranchi, the collected subjective prisoner behavioral responses were transcribed into numerical scores. The entire set of 57 behavioral attributes are made up of 20 HCR-20 delinquent behavioral characteristics, and fifty seven other attributes that span both clinical and non clinical risk factors for recidivism behavioral assessments. Furthermore, the behavioral response score for each of the 20 items in HCR-20 was marked as either 0(absent), 1(minor or moderately present) or 2 (definitely present), and the total scores for HCR-20 ranged from 20 to 40 respectively. The predictive validity and efficacy of HCR-20 is between (0.71-0.74) [30], [32]. Additionally, the responses for the remaining 37 attributes were also marked similarly based on inputs from domain experts on a scale of three.

D. FEATURE SELECTION

Standard statistical feature selection technique viz. ANOVA has been used to identify relevant attributes for the current data set. ANOVA examines group variances and means to determine whether the means are overlapping. In this regard, if the observed differences are found to be substantial, the features are believed to be statistically significant, resulting in a lower p value. In this study, the p-value has been defined as 0.05, indicating that the attributes are statistically significant. A total of 57 features have been found to be statistically significant out of 65 with p value less than 0.05. Table 5 and 6 depicts a summarized overview of different types of significant and insignificant features. Identified significant features for each individual are fed to an ensemble of classifiers [33]–[35]. Such a model will facilitate in the automatic assessment of first-time offenders into three recidivism risk groups: low, moderate, and high.

E. CLASSIFICATION

Different classifiers are used in pattern recognition to partition the feature vector (space) into class labeled decision regions according to feature similarities. Moreover, in all pattern classification problems, each individual feature vector is allocated a label (viz. class/group), a predetermined integer value based on the classification model output, and the total number of available classes. The weights of each classifier must be modified to obtain the desired set of target outputs for any given set of inputs. The overall volume of data collected was split into two categories: training and testing. The neural network weights are updated using the difference between the desired output (training data) and the predicted output, and this process is known as training. These specialised techniques that are used to update the network weights are referred to as learning algorithms. Moreover, the rest of the dataset is referred to as testing data, and it is used to verify the classifier's performance. In the present study, we suggest the use of an ensemble classifier model along with behavioral risk factors for the prediction of recidivism risk (i.e. low, moderate and high) among first-time offenders. Five other standard classifiers, viz. naive Bayes blassifier (NBC) [36], k-Nearest neighbor (KNN) [37], multilayer perceptron network (MLP) [38], probalistic neural network (PNN) [39] and support vector machine(SVM) [40] were used to assess classification performance for both clinical and non-clinical recidivism risk factors. Each classifier's parameters were fine-tuned to achieve maximum accuracy, and the same dataset (both training and testing) was used to evaluate each classifier's output.

1) ENSEMBLE OF CLASSIFIERS

A combination of multiple classifiers that generates various hypotheses using the same base learner is referred to as an ensemble of classifiers [41], [42]. Ensemble methods are powerful machine learning techniques that combine multiple base models to create a single best-fit predictive model. Such models combine the decisions of multiple classifiers to achieve the best precision, variance, and bias and can solve complex nonlinear problems [43]. The most popular ensemble techniques include averaging, bagging, boosting, and stacking. Ensemble models are favoured over individual classifier models for a number of reasons, as discussed below [35].

i. Reduces the likelihood of poor feature selection
ii. Offers an extra degree of freedom for complicated problems that a single classifier cannot solve.

iii. This lessens the issue of overfitting.
iv. Useful with heterogeneous features

Achieving classifier diversity is an essential characteristic that is desirable for all ensemble learning models. This is achieved through a number of techniques, including the use of multiple datasets, individual training parameters, and a combination of a complex range of classifiers. To construct a specific diverse ensemble model, it is often important to have a set of classifiers with sufficiently different decision surfaces. Thus, a suitable classifier combination policy and ensemble construction must be permanently configured so that the potential for correct decisions is strengthened, while the possibility off misclassification is eliminated.

Another essential consideration when aggregating classifiers is the formulation of appropriate combination rules. Classifier combination methods, which apply only to generated class labels and are based on model decision performance, are one such technique. To estimate the final ensemble class label, the outputs (class labels) from the individual base classifier members are merged. To compute the final ensemble class label from the individual class labels, explicit predetermined rules have already been formulated and are in practice. The most basic classifier combination methods add some fixed functions to all of the generated ensemble classifier outputs, such as majority voting, bagging and Borda count [44]. Boosting and stack generalization are more complex based classifier selection approaches that aim to select only specific classifiers that will contribute to the ensemble. The majority voting-based combination rule tends to be the most basic and effective and has been incorporated in the present work.

F. ENSEMBLE CLASSIFIER MODEL FOR RECIDIVISM RISK ASSESSMENT

Obtaining a low error rate with a single classifier model is extremely difficult for the current automated recidivism risk assessment problem. As a result, a multiple classifier (ensemble) model was implemented for recidivism risk assessment to achieve higher classifier accuracy and robust performance. To predict the best feature performance, an ensemble-based approach combines different diverse base classifiers (weak learners) to predict the best feature performance. Classifier diversity can be accomplished by applying an exclusively distinctive set of classifiers, and using a distinct collection of training data for each weak learner (base classifier) [45]. Moreover, because each base classifier can produce a unique decision boundary and error, the objective here is to combine relevant classifiers to reduce the overall error. The bagging ensemble approach is used to achieve classifier diversity in the present work by training each base classifier (ensemble member) using a stochastically selected subgroup of the training results. The individual base classifier outputs are consolidated using principle of majority voting. The final ensemble decision is determined based on the class labels specified by the maximum number of base classifiers. Figure 2 shows a generalised ensemble classifier framework for feature classification.

TABLE 7. **Confusion matrix for automated recidivism risk assessment.**

Classifier		Actual(Psychologist)		
		A (Low)	B (Moderate)	C(High)
	A (Low)	TP_{AA}	E_{BA}	E_{CA}
Predicted	B (Moderate)	E_{AB}	TP_{BB}	E_{CB}
(Model Output)	C (High)	E_{AC}	E_{BC}	TP_{CC}

In general, there are two different methods for constructing classifier ensembles. As a result, when building an ensemble model, we either use a single weak learner (base classifier) with flexible configurations and parameterizations as base members or use various independent base classifiers. In this study, we investigated the second alternative: constructing an ensemble of classifiers by combining multiple classifiers with multiple constraints. As a result, we suggest a three-member and a five-member ensemble model for automated recidivism risk assessment, EOC_3 is made up of three separate classifiers: MLP, SVM, and NBC, while EOC_5 is made up of five different classifiers: KNN, MLP, SVM, NBC, and PNN. The experimental results of both the ensemble models are presented in Section V.

IV. PERFORMANCE ANALYSIS AND VALIDATION

Because the amount of data gathered for the proposed investigation was restricted, the k-fold cross-validation [46] re-sampling procedure was followed to train and test the reoffending features for recidivism risk assessment. Presuming the value of k to 5, the original dataset was divided into five sections at random, with every class, represented approximately in the same proportions as in the primary dataset. In the first instance, the first fold is used to evaluate the model, while the other folds are used to train the model. Similarly, in the second iteration, the second fold was used as the testing set, while the remaining folds were used as the training examples. This procedure was repeated 5 times until each of the five folds was verified as testing set. Moreover, the overall classifier performance was assessed based on the average accuracy, precision, true positive rate (TPR), and false positive rate (FPR), as determined by solving the confusion matrix. The disparity in assessment between the psychologist and classifier model is represented using a confusion matrix (Table 7) and is deployed for performance evaluation in automated recidivism risk assessment.

Table 7 depicts a confusion matrix for a multiclass classification problem with three levels of recidivism risk observed among first-time offenders: A (low), B (moderate), and C (high). Here, TP_{AA} signifies the proportion of true positive observations in class A (Low), i.e., if the sample is actually A(low) and it is also predicted as A(low). Whereas, E_{AB} represents the specimens from class A (low) that are falsely predicted as class B(moderate). In a multiclass classification

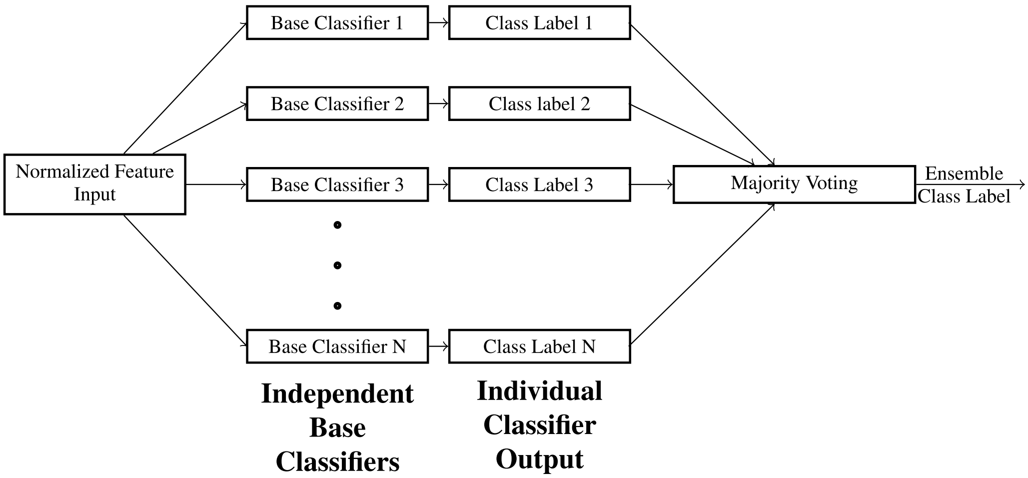

FIGURE 2. A generalised ensemble classifier framework with majority voting.

problem the false negative in the A-class (FN_A) is represented as the sum of E_{AB} and E_{AC}. Where, FN_A (E_{AB} + E_{AC}) indicates the sum of all class A samples that were incorrectly classified as class B or C. Whereas, false positive in class A (FP_A) is depicted as all class B and C samples that were incorrectly classified as class A. FP_A is computed as the sum of E_{BA} and E_{CA}

In this research, evaluation methods, i.e., accuracy, precision, specificity (FPR or specificity) and sensitivity (TPR or recall) are estimated to evaluate the results of the above classifiers and can be formulated as follows:-

$$Accuracy = \frac{Correctly\ \ Classified\ \ Samples}{Total\ \ no.\ \ of\ \ Samples} \times 100$$

$$Precision = \frac{Correctly\ \ Classified\ \ Samples}{Total\ \ Correctly\ \ Classified\ \ Samples\ \ of\ \ all\ \ Class} \times 100$$

$$Sensitivity = \frac{Positive\ \ Correctly\ \ Classified\ \ Samples}{Total\ \ no.\ \ of\ \ Positive\ \ Samples} \times 100$$

$$Specificity = \frac{Correctly\ \ Classified\ \ Negative\ \ Samples}{Total\ \ no.\ \ of\ \ Negative\ \ Samples} \times 100$$

Another efficiency metric for determining the classification potential is the receiver operating characteristic (ROC) curve. The learning procedure is run five times on different folds of the training sets, with classification accuracy, precision, specificity, and sensitivity being documented each time. Finally, each measure's overall estimate was calculated by averaging all five readings.

V. EXPERIMENTAL RESULTS AND DISCUSSION

In this study, an ensemble machine learning framework was developed to determine the likelihood of recidivism among first-time offenders in the Indian state of Jharkhand. The proposed system was implemented using MATLAB R2012B, and experimental simulations were conducted on an Intel Core i5 processor and 8GB of RAM running Windows 10 Pro operating system.

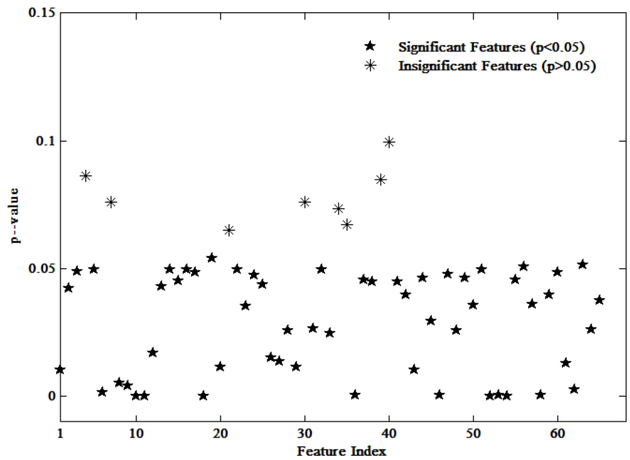

FIGURE 3. Gscatter plot for p value and feature index to obtain significant features.

First-time offenders are judged based on the existence or absence of a variety of risk factors, including their deviant conduct. Based on these evaluations, offenders could be characterized as low, moderate and serious (high) risk based on the presence or absence of a specific clinical and non-clinical attributes. In this study, the offenders were interviewed and a data set based on standard principles was created, as presented in Section III-A. After feature selection (dataset creation), the discriminant features are identified using statistical feature selection technique viz. ANOVA. Using ANOVA, 57 discriminating attributes were identified for feature classification.

A plot between individual features (feature index) and and its corresponding p-values is depicted in Figure 3,which indicates significance of the features to discriminate between

TABLE 8. Average prediction (classification) accuracy of standard classifiers along with ensemble models over 5-fold.

Classifier	k-fold Cross Validation					Average Accuracy(%)
	k=1	k=2	k=3	k=4	k=5	
MLP	62.50	75.00	68.75	83.33	68.75	71.66
PNN	56.25	68.75	75.00	62.50	83.33	69.16
NBC	68.75	62.50	75.00	83.33	75.00	72.91
KNN	62.50	75.00	66.67	83.33	68.75	71.25
SVM	75.00	68.75	83.33	75.00	83.33	77.08
*$\mathbf{EOC_3}$	90.91	83.33	81.82	80.38	90.91	**85.47**
*$\mathbf{EOC_5}$	91.67	90.91	83.33	90.90	81.82	**87.72**

* Proposed

TABLE 9. Average precision and recall of standard classifiers along with ensemble models over five fold.

Classifier	Performance	k–fold Cross Validation					Average
		k=1	k=2	k=3	k=4	k=5	
MLP	Precision	0.62	0.66	0.60	0.62	0.58	0.62
	Recall	0.62	0.72	0.64	0.66	0.58	0.64
PNN	Precision	0.58	0.64	0.71	0.76	0.75	0.68
	Recall	0.59	0.62	0.72	0.74	0.78	0.69
NBC	Precision	0.74	0.76	0.72	0.83	0.58	0.72
	Recall	0.76	0.78	0.70	0.80	0.62	0.73
KNN	Precision	0.58	0.64	0.63	0.76	0.62	0.64
	Recall	0.58	0.62	0.64	0.74	0.66	0.64
SVM	Precision	0.67	0.74	0.67	0.64	0.74	0.68
	Recall	0.68	0.74	0.68	0.70	0.74	0.71
*$\mathbf{EOC_3}$	Precision	0.84	0.83	0.79	0.88	0.86	**0.84**
	Recall	0.82	0.80	0.78	0.86	0.85	**0.82**
*$\mathbf{EOC_5}$	Precision	0.83	0.85	0.91	0.89	0.86	**0.86**
	Recall	0.80	0.82	0.90	0.88	0.84	**0.84**

* Proposed

TABLE 10. Average prediction (classification) accuracy of standard classifiers along with the proposed ensemble models over five fold for socio–demographic factors.

Classifier	k—fold Cross Validation					Average Accuracy(%)
	k=1	k=2	k=3	k=4	k=5	
MLP	63.75	56.25	73.68	78.57	64.28	67.30
PNN	73.68	66.67	64.28	71.42	57.14	66.63
NBC	68.42	78.57	71.42	66.00	71.42	71.16
KNN	63.15	68.42	71.42	75.00	66.67	68.93
SVM	71.42	64.28	78.57	67.67	78.57	72.02
*$\mathbf{EOC_3}$	78.57	83.33	71.42	85.71	66.67	**77.14**
*$\mathbf{EOC_5}$	83.33	85.71	78.57	71.42	78.57	**79.52**

* Proposed

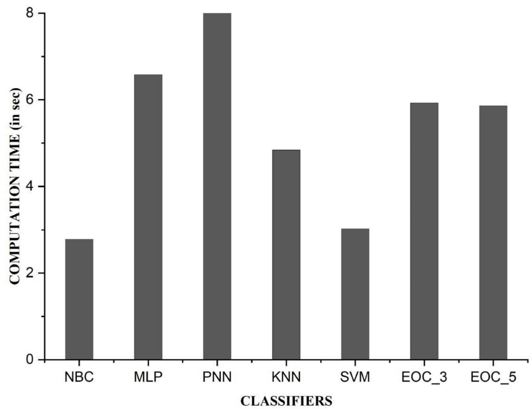

FIGURE 4. Variation of computation times.

two groups. The basis for recidivism risk assessment data for FTOs is the selected set of 57 attributes representing a combination of individual, family, socio-demographic and other risk factors. Experiments were conducted using the attributes, and the sample offenders in the dataset were characterized into three risk groups using the proposed three and five classifier ensemble models. In addition, the k-fold cross-validation for the training/testing data partitioning was followed for a fair assessment of the proposed automated recidivism assessment model. A comparative recidivism risk assessment with ensemble model standard base classifiers that is, NBC, KNN, MLP, PNN and SVM was analyzed with the same set of 57 attributes. The average prediction performance with respect to recognition (classification) accuracy, precision and recall of traditional base classifiers along with ensemble model are presented in Table 8 and Table 9 respectively. Furthermore, to provide a comparative study, the average predictive performance (classification accuracy) of ensemble methods and conventional classifiers using socio-demographic factors is tabulated in Table 10.

In addition, for all the above classifiers, the execution time (in seconds) of the entire classification process (training and testing phases) was recorded and is presented in Figure 4.

Our experimental observations show that the average precision is between the range (0.62–0.72) for individual base classifiers (MLP, PNN, NBC, KNN, SVM), whereas the recall for these classifiers is reported to be between (0.64–0.73). However, the best overall precision of 0.86 and an average recall of 0.84 is achieved with five-member ensemble model for the available datasets with 5-fold cross-validation. The corresponding average accuracy was also calculated as 87.72 with EOC_5 for both clinical and non-clinical risk factors. An average accuracy of 79.52 was recorded with EOC_5 for socio-demographic factors. To summarize EOC_5, we observed both precision and recall more than 80% in all 5-folds consistently, and the average accuracy of all folds was found to be higher than that of 85%. A marginally higher average computation time for the proposed ensemble model was recorded with respect to the other base classifiers. As a result, the proposed model can support a real-time recidivism risk assessment system for first-time offenders.

VI. CONCLUSION AND FUTURE WORK

Recidivism refers to a person's recurrence in criminal behavior, often following the imposition of sanctions or intervention for a prior crime. It facilitates law enforcement bodies in making decisions on criminal convictions, parole eligibility, and framing of correctional policy for first-time offenders. In addition, it is also necessary to ensure proper measures for offenders and their reintegration into the society through vocational training. Early screening of recidivism behavior is vital and it can have a significant impact on the rehabilitation plan for convicted FTOs. Behavioral sampling of FTOs by a criminologist using standard HCR-20 is often sluggish, qualitative, and inconsistent. In contrast, the machine learning-based approach to identify recidivists is quantitative and offers a precise screening mode. Therefore, the proposed study uses machine learning to assess the risk of recidivism among first-time offenders. Demographic and socio-economic behavioral traits and a questionnaire based on a customized HCR-20 scale were used to measure different aspects of psychological characteristics with respect to recidivism. Individualized FTO data were gathered from various prisons in the Indian state of Jharkhand and then standardized by a panel of psychologists. The dataset includes 10 personality, 16 demographic, 8 parental and family, 11 socio-economic and environmental variables, as well as 20 HCR-20 traits. The use of an ensemble of classifiers to develop an automated screening system for early recidivism assessment among FTOs is the key issue of this study. In comparison to individual classifiers, both the proposed three and five-member ensemble classifier models showed encouraging classification accuracy. A predictive accuracy of 87.72% was observed using five-member ensemble model. For the available data, the average sensitivity and specificity were both higher than 85%. The findings of this work inspire future research, such as the classification of FTOs recidivism behavior concerning heinous crime.

REFERENCES

[1] S. Vago, A. Nelson, V. Nelson, and S. E. Barkan, *Law and Society: Canadian Edition*. Evanston, IL, USA: Routledge, 2017.

[2] C. D. Webster, K. S. Douglas, D. Eaves, and S. D. Hart, "Assessing risk of violence to others," in *Impulsivity: Theory, Assessment, and Treatment*, pp. 251–277, 1997.

[3] S. Jacques, "The quantitative–qualitative divide in criminology: A theory of ideas importance, attractiveness, and publication," *Theor. Criminol.*, vol. 18, no. 3, pp. 317–334, 2014.

[4] R. Aljumily, "Quantitative criminology: An evaluation of sources of crime data," *Global J. Hum. Social Sci.*, vol. 16, no. 4, 2016.

[5] D. McDowall, "The present and possible future of quantitative criminology," *J. Quant. Criminol.*, vol. 26, no. 4, pp. 429–435, Dec. 2010.

[6] A. Buchanan, R. Binder, M. Norko, and M. Swartz, "Resource document on psychiatric violence risk assessment," *FOCUS*, vol. 13, no. 4, pp. 490–498, Oct. 2015.

[7] L. Mandate, "Recidivism and the 'first offender' U.S.Sentencing commission," Tech. Rep., 2004.

[8] P. D. Scott, "Recidivism: A deficiency disease. By A. W. Macleod. Philadelphia: University of Pennsylvania Press. 1965. Pp. 131. Price not stated," *Brit. J. Psychiatry*, vol. 112, no. 491, pp. 1085–1086, 1966.

[9] R. Berk, "Algorithmic criminology," *Secur. Informat.*, vol. 2, no. 1, p. 5, Dec. 2013.

[10] C. L. Valentine, C. Hay, K. M. Beaver, and T. G. Blomberg, "Through a computational lens: Using dual computer-criminology degree programs to advance the study of criminology and criminal justice practice," *Secur. Informat.*, vol. 2, no. 1, pp. 1–7, Dec. 2013.

[11] P. Das, A. K. Das, J. Nayak, D. Pelusi, and W. Ding, "Incremental classifier in crime prediction using bi-objective particle swarm optimization," *Inf. Sci.*, vol. 562, pp. 279–303, Jul. 2021.

[12] G. Hajela, M. Chawla, and A. Rasool, "A clustering based hotspot identification approach for crime prediction," *Proc. Comput. Sci.*, vol. 167, pp. 1462–1470, Jan. 2020.

[13] C. Catlett, E. Cesario, D. Talia, and A. Vinci, "Spatio-temporal crime predictions in smart cities: A data-driven approach and experiments," *Pervas. Mobile Comput.*, vol. 53, pp. 62–74, Feb. 2019.

[14] A. Ghazvini, S. N. H. S. Abdullah, M. K. Hasan, and D. Z. A. B. Kasim, "Crime spatiotemporal prediction with fused objective function in time delay neural network," *IEEE Access*, vol. 8, pp. 115167–115183, 2020.

[15] R. Wortley and L. Mazerolle, "Environmental criminology and crime analysis: Situating the theory, analytic approach and application," *Crime Prevention Community Saf., Int. J.*, vol. 11, pp. 23–40, Apr. 2009.

[16] T. Bosse, C. Gerritsen, and J. Treur, "On the relation between cognitive and biological modelling of criminal behaviour," *Comput. Hum. Behav.*, vol. 27, no. 5, pp. 1593–1611, Sep. 2011.

[17] U. Merlone, E. Manassero, and G. Zara, "The lingering effects of past crimes over future criminal careers," in *Proc. Winter Simulation Conf. (WSC)*, Dec. 2016, pp. 3532–3543.

[18] M. Agrawal, J. C. Peterson, and T. L. Griffiths, "Using machine learning to guide cognitive modeling: A case study in moral reasoning," Princeton Univ., Princeton, NJ, USA, Tech. Rep., 2019.

[19] J. Caulkins, J. Cohen, W. Gorr, and J. Wei, "Predicting criminal recidivism: A comparison of neural network models with statistical methods," *J. Criminal Justice*, vol. 24, no. 3, pp. 227–240, Jan. 1996.

[20] N. Z. Hilton, G. T. Harris, and M. E. Rice, "Sixty-six years of research on the clinical versus actuarial prediction of violence," *Counseling Psycholog.*, vol. 34, no. 3, pp. 400–409, May 2006.

[21] A. R. Piquero, W. G. Jennings, B. Diamond, and J. M. Reingle, "A systematic review of age, sex, ethnicity, and race as predictors of violent recidivism," *Int. J. Offender Therapy Comparative Criminol.*, vol. 59, no. 1, pp. 5–26, Jan. 2015.

[22] F. T. Ngo, R. Govindu, and A. Agarwal, "Assessing the predictive utility of logistic regression, classification and regression tree, chi-squared automatic interaction detection, and neural network models in predicting inmate misconduct," *Amer. J. Criminal Justice*, vol. 40, no. 1, pp. 47–74, Mar. 2015.

[23] S. Wijenayake, T. Graham, and P. Christen, *A Decision Tree Approach to Predicting Recidivism in Domestic Violence*. Springer, 2018.

[24] F. Yang, C. Wu, N. Xiong, and Y. Wu, "Prediction of criminal tendency of high-risk personnel based on combination of principal component analysis and support vector machine," *Int. J. Softw. Hardw. Res. Eng.*, vol. 6, no. 8, pp. 1–10, 2018.

[25] C. Wang, B. Han, B. Patel, F. Mohideen, and C. Rudin, "In pursuit of interpretable, fair and accurate machine learning for criminal recidivism prediction," 2020, *arXiv:2005.04176*. [Online]. Available: http://arxiv.org/abs/2005.04176

[26] J. van Dijk, S. Kalidien, and S. Choenni, "Smart monitoring of the criminal justice system," *Government Inf. Quart.*, vol. 35, no. 4, pp. S24–S32, Oct. 2018.

[27] R. Berk, "An impact assessment of machine learning risk forecasts on parole board decisions and recidivism," *J. Experim. Criminol.*, vol. 13, no. 2, pp. 193–216, Jun. 2017.

[28] A. Završnik, "Algorithmic justice: Algorithms and big data in criminal justice settings," *Eur. J. Criminol.*, vol. 18, no. 5, pp. 623–642, Sep. 2021.

[29] C. Morselli, V. H. Masias, F. Crespo, and S. Laengle, "Predicting sentencing outcomes with centrality measures," *Secur. Informat.*, vol. 2, no. 1, pp. 1–9, Dec. 2013.

[30] A. Nijdam-Jones, E. García-López, L. Merchan-Rojas, A. Ruiz Guarneros, and B. Rosenfeld, "Predictive validity of the HCR-20^{V3} with incarcerated males in Mexico City," *Criminal Justice Behav.*, Mar. 2021, Art. no. 0093854821997520.

[31] N. S. Gray, J. Taylor, and R. J. Snowden, "Predicting violent reconvictions using the HCR-20," *Brit. J. Psychiatry*, vol. 192, no. 5, pp. 384–387, May 2008.

[32] M. Yang, S. C. Wong, and J. Coid, "The efficacy of violence prediction: A meta-analytic comparison of nine risk assessment tools," *Psychol. Bull.*, vol. 136, no. 5, p. 740, 2010.

[33] D. Qiu and J. Ahn, "Grouped variable screening for ultra-high dimensional data for linear model," *Comput. Statist. Data Anal.*, vol. 144, Apr. 2020, Art. no. 106894.

[34] W.-L. Wang, L. M. Castro, V. H. Lachos, and T.-I. Lin, "Model-based clustering of censored data via mixtures of factor analyzers," *Comput. Statist. Data Anal.*, vol. 140, pp. 104–121, Dec. 2019.

[35] R. Polikar, "Ensemble based systems in decision making," *IEEE Circuits Syst. Mag.*, vol. 6, no. 3, pp. 21–45, Sep. 2006.
[36] R. Duda, D. Hart, and P. Stork, *Pattern Classification*, 2nd ed. Hoboken, NJ, USA: Wiley, 2007.
[37] T. Acharya and A. K. Ray, *Image Processing Principles and Applications*. Hoboken, NJ, USA: Wiley, 2005.
[38] S. Feng, L. Li, L. Cen, and J. Huang, "Using MLP networks to design a production scheduling system," *Comput. Oper. Res.*, vol. 30, no. 6, pp. 821–832, May 2003.
[39] P. P. Raghu and B. Yegnanarayana, "Supervised texture classification using a probabilistic neural network and constraint satisfaction model," *IEEE Trans. Neural Netw.*, vol. 9, no. 3, pp. 516–522, May 1998.
[40] G. Duwe and K. Kim, "Out with the old and in with the new? An empirical comparison of supervised learning algorithms to predict recidivism," *Criminal Justice Policy Rev.*, vol. 28, no. 6, pp. 570–600, Jul. 2017.
[41] L. K. Hansen and P. Salamon, "Neural network ensembles," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 12, no. 10, pp. 993–1001, Oct. 1990.
[42] G. Brown and L. I. Kuncheva, "'Good' and 'bad' diversity in majority vote ensembles," in *Proc. Int. Workshop Multiple Classifier Syst.* Berlin, Germany: Springer, 2010, pp. 124–133.
[43] Z.-H. Zhou, *Ensemble Methods: Foundations and Algorithms*. London, U.K.: Chapman & Hall, 2012.
[44] M. Mohandes, M. Deriche, and S. O. Aliyu, "Classifiers combination techniques: A comprehensive review," *IEEE Access*, vol. 6, pp. 19626–19639, 2018.
[45] C. Zhang and Y. Ma, *Ensemble Machine Learning: Methods and Applications*. Boston, MA, USA: Springer, 2012.
[46] A. Krogh and J. Vedelsby, "Neural network ensembles, cross validation, and active learning," in *Proc. Adv. Neural Inf. Process. Syst.*, 1995, pp. 231–238.

AMAN SINGH received the B.E. degree in computer science and engineering (CSE) from St. Peters University, Chennai, and the M.E. degree in information technology (IT) from Savitribai Phule Pune University, Pune, India, in 2016. He is currently a Research Scholar with the Department of Computer Science and Engineering, Birla Institute of Technology, Mesra (BIT Mesra), Ranchi. His current interests include cognitive science, data analytics, and pattern recognition.

SUBRAJEET MOHAPATRA received the B.E. degree in computer science and engineering (CSE) from Sambalpur University, Sambalpur, and the M.Tech. degree in computer science and the Ph.D. degree in electronics and communication engineering from the National Institute of Technology Rourkela, Odisha, in 2008 and 2012, respectively. He is currently working as an Assistant Professor with the Department of Computer Science and Engineering, Birla Institute of Technology, Mesra (BIT Mesra), Ranchi. His research interests include image processing, cognitive science, pattern recognition, cloud computing, and soft computing.