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ORIGINAL RESEARCH

# Support vector machine-based handover scheme for heterogeneous ultra dense network of high-speed railway

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**Abstract**

In order to meet the growing demands and extend network coverage for high-speed railway (HSR) system, the dense deployment of a large number of small cells (SCs) is considered for 5G networks. However, the deployment of dense SCs and the high speed of trains result in challenging problems such as interference, frequent handovers (HOs), increased HO failure rate, and consequently the deteriorated overall quality of service (QoS). In order to address the challenges in handover, an improved handover decision strategy is proposed based on Support Vector Machine (SVM). The HO decision making is considered as a classification problem taking into account available states that they may have in the HSR network. From the simulation results, it is observed that the proposed scheme is capable of decreasing the number of HO, HO failure rate and enhancing the network performance remarkably.

## 1 | INTRODUCTION

High-speed railways have emerged as a transformative mode of transportation, revolutionizing the way people and goods move across long distances. With their remarkable speed, efficiency, and environmental advantages, HSRs have gained significant popularity and are becoming a vital form of transportation. As the demand for fast, reliable, and sustainable transportation grows, effective management of HSR mobility becomes crucial to ensure smooth operations and enhance passenger experience. Thus, how to provide users with the best quality of high-speed mobile network services attracts increasing attention in the research of fifth-generation (5G) wireless communications. One of the big challenges is the handover problem, such as the frequent handover, unnecessary handover etc. due to the increased density of small cells and increased speed of trains [1, 2]. Handover refers to the transfer of an ongoing call or data session from one cell to another cell while maintaining the QoS. Railway communications systems are crucial for safe train operations, which require real-time information, coordination and emergency communication. Interruptions during handover can impact continuous connectivity and data integrity, potentially leading to safety risks such as data loss. Thus, seamless handover procedures in HSR is very vital to ensure reliable communications.

Ultra-dense network (UDN) is deployed in 5G-Railway to meet the increasing demand of mobile internet services of large number of train passengers. UDN in wireless communications refers to a network of BSs deployed at an extremely high density, often with inter-site distances of tens to hundreds of meters [3]. This high density leads to a significant increase in the number of BSs per unit area compared to traditional cellular networks. In addition, millimeter-wave (mmWave) is considered as a promising technique used in the 5G communication for UDN. However, both the small coverage of mmWave and the ultra-dense small cells can result in more severe frequent HO problem. Frequent HO causes disruption of data service, higher signaling overhead and decreased network throughput. Moreover, most of the high-speed trains have metal bodies with large windows of a single layer or multi-layer glasses, which cause great attenuation for high frequency signals. Additionally, handover failure occurs if the user equipments (UEs) fail to connect to the target cell, especially in the ultra-dense network using the mmWave which offers high data rates but experiences higher propagation loss. This means that the signal strength degrades rapidly over distance. As a user moves away from a base station (BS), the signal strength drops quickly, increasing the probability of handover failure. In ultra-dense networks, a large number of small cells are deployed in a limited geographical area, leading to increased interference levels. Co-channel interference can hinder seamless handover and decrease the received signal strength leading to handover failure. Thus, handover problem is becoming more serious in the UDN of HSR that must be addressed.

## 1.1 | Related work

There already exist several different schemes which solve the HO problems mentioned above. The work in [4] adopts a gray model prediction based handover scheme to prevent the handover delay problem, and they used a combination factor in the handover decision-making to select the best target cell in heterogeneous UDN for HSR. Reference [5] provides an in-depth survey of channel modeling in HSR communication systems. It discusses the requirements for future HSR channel models, such as multi-link cross-correlations, mmWave technology, massive MIMO-related properties and generality. Additionally, it outlines potential research directions for future HSR channel modeling, emphasizing the importance of utilizing deep learning to achieve intelligent channel modeling.

Further, the authors of [6] adopt a dual-link soft handover algorithm by deploying a train relay station (TRS) and two antennas on top of train to decrease the outage probability of handover for control/user (C/U) plane split network. In [7], a handover scheme for UE devices, which are located on platforms in a train station is introduced. These UE devices are allowed to connect to mobile relays (MRs) inside the train to reduce network loads. The network makes handover decisions based on the relative velocities between trains and UE devices (the relative velocities change when trains are approaching to, leaving from, and staying in stations). The works in [8, 9] propose MRs as a solution to improve communication quality by reducing handover delays.

Reference [10] provides a comprehensive overview of the current state-of-the-art and future trends for exploring the utilization of mmWave technology for high-speed railway communication systems. In [11] and [12], different handover schemes based on 5G mmWave mobile communication systems in the HSR scenario are proposed. Work in [11], the authors present a novel approach to improve inter-beam handover (IBH) in HSR scenarios for 5G mmWave communication systems. Simulation results show that the proposed method can decrease handover failure rates and achieve a balance between handover failure and resource occupation rates in the HSR scenario. In [12], the authors propose a Long Short-Term Memory (LSTM) based method to improve handover in 5G mmWave networks for high-speed railways. This method aims to address the high handover delay and link interruption issues of the traditional A3 handover approach. In [13], authors proposed a handover optimization method that utilizes fuzzy logic to decrease the number of HOs. Their simulation results demonstrate that the ping-pong effect has been significantly reduced.

With the development of 5G and beyond networks, artificial intelligence (AI) will play a crucial role in many innovative 5G technologies and architectures in the future. The main reason is that AI techniques are increasingly being utilized in wireless communication due to their powerful learning and optimizing ability to analyze complex data patterns, make intelligent decisions, and adapt to dynamic environments [14]. Additionally, machine learning (ML) techniques can be used to refine the models by analyzing the behavioral traits of moving objects from historical records and predicting future movements using trained models. For handover management, it can be used to achieve intelligent mobility prediction and optimal handover solutions to guarantee seamless communication connectivity. An intelligent mobility management system based on an improved multi-objective optimization method by ratio analysis (E-MOORA) and reinforcement learning approach has been discussed in [15]. In this scheme, authors first adopt the E-MOORA method to decrease the ranking abnormality when it selects a target BS. Reinforcement learning method is used to select the optimal triggering points, aiming to reduce the number of frequent HOs and handover failure rate for better QoS. However, the authors only consider handover occurring in an intra-macro cell scenario. In [16], authors propose and evaluate a ML-based handover algorithm to improve users' QoS in the presence of signal-blocking obstacles. Their simulation results demonstrate that the proposed scheme is able to choose the BS that will provide the highest QoS, even in severe channel propagation situations. Nevertheless, they do not consider the effect of velocity on handover performance. Work on [17] uses the received power of the serving and the target BS as input feature for handover failure prediction based on a machine learning model. However, they do not consider the effect of interference which is severe in UDN. In [18] and [19], different machine learning approaches are applied for future mobility prediction. Machine learning based user-level handover decision making scheme in 3GPP networks is presented in [18], where the authors employ various classification algorithms, including neural networks, to address the problem of identifying the optimal HO target BS. They also utilize regression approaches to estimate the duration and percentage of download progress of a mobile user, specifically when the user is in motion and has initiated a HO request. In [19], a novel framework is introduced to predict the future network connection of a mobile node in WLAN environments. The proposed framework incorporates a decision-making process that relies on classification algorithm, as well as the user's position and acceleration data, to anticipate network change. The proposed method achieves an impressive prediction accuracy of up to 96.75% when forecasting the connection of the future network. A Bayesian regression based LTE-R handover decision algorithm [20] for HSR is proposed to predict the cell boundary crossing time. Their proposed method maintains stronger signal strength between MRs and the serving BS both before and after the handover. This improvement results in a reduced likelihood of radio link failure

(RLF). However, they do not consider the Doppler shift effect in HSR scenario.

Despite the improvements achieved by the existing works, they may not perform efficiently in 5G HSR mmWave UDNs. This is primarily due to the challenges posed by the small coverage area and high propagation loss of the mmWave technique. Therefore, the HO challenges cannot be solved by other existing methods for 5G HSR mmWave UDNs. In order to fill this gap, this paper focuses on investigating handover performance enhancement using various machine learning algorithms in 5G mmWave ultra-dense network of HSR. Leveraging the characteristics of HSR scenario, the study develops a SVM-based prediction method to find the optimal target cell. More specifically, the objective of our proposed scheme is to decrease the number of HO, HO failure probability and enhance the network performance. This approach takes into account a range of appropriate handover criteria and the Doppler effect to enhance handover performance and deliver satisfying QoS to train users of HSR system.

### 1.2 | Contribution

In this paper, we develop an efficient intelligent HO scheme based on machine learning algorithms for 5G heterogeneous ultra-dense network of high-speed railways. In a dense 5G HSR deployment, HO decision can be optimized by utilizing support vector machine algorithm in order to reduce the number of HOs and improve the network performance. The proposed SVM-based handover scheme determines the optimal hyperplane using labeled training data to classify the available target cells by jointly considering multiple HO criteria such as reference signal received power (RSRP), signal to interference plus noise ratio (SINR) and time. In addition, we conduct extensive simulations to demonstrate the effectiveness of our proposed SVM-based HO scheme and demonstrate that the proposed scheme can improve the HO performance in terms of the number of HOs, handover failure probability and user mean throughput compared to other machine learning approaches and existing methods in the literature. The contributions of this research are recapped as follows:

- We develop an intelligent handover scheme based on SVM algorithm which selects the target cell by jointly considering multiple HO criteria.
- We introduce the standard deviation (SD) technique to assess the priority weight and effect of different attributes in BS selection algorithm.
- We also incorporate the effect of Doppler shift into our HSR system model to simulate a more realistic railway system.

The rest of the paper is organised as follows. Section 2 introduces the network architecture model and usage scenarios. In Section 3, we present a brief introduction of the SVM algorithm and then the proposed SVM-based HO scheme is explained in Section 4. In Section 5, simulation results are shown and the performance of the proposed method are evaluated and compared with other approaches. Finally, Section 6 concludes this paper.

## 2 | SYSTEM MODEL

### 2.1 | HSR network architecture

In this paper, we consider a heterogeneous UDN deployed for high-speed railway, as depicted in Figure 1. The network consists of two layers. The first layer utilizes macro BS operating at a carrier frequency of 2GHz to ensure uninterrupted coverage. The second layer employs small BS operating at mmWave frequency, which offers high-speed data services to passengers thanks to their abundant bandwidth resources. Thus, the mmWave technology can support a massive number of connected devices simultaneously, especially in HSR environments. However, the mmWave signal suffers from high path loss and significant propagation attenuation, resulting in limited coverage [21]. Consequently, a dense deployment of small BS is required in the HSR scenario.

To mitigate penetration loss caused by trains, a relay station is deployed on the train's roof. This relay assists passengers in connecting to the small BS or macro BS located along the track side. Passengers can access the Internet through access points connected to the train relay station via wired link. The TRS acts as a single entity to execute HO from the serving BS to the target BS, aiming to minimize handover signaling overhead and avoid the penetration loss caused by the train.

### 2.2 | Channel model

In this paper, the linear radio coverage topology is adopted in HSR and only the main path signal is considered since high-speed train runs through rural or viaduct areas most of the time, so multi-path effect can be ignored. At time $t$, let a high-speed train be located at position $x$ in the $i$-th BS. The received signal power as well as RSRP from the BS $i$ is considered in dBm as follows:

$$RSRP(i,x)[\text{dBm}] = Pt[\text{dBm}] - PL(i,d_i)[\text{dB}] - \zeta(0,\sigma_i)[\text{dB}], \tag{1}$$

where $Pt$ is the transmission power of the $i$-th BS. $PL\ (i, d_i)$ is the path loss. $\zeta\ (0, \sigma_i)$ is a Gaussian distributed random variable with a zero mean and a standard deviation to describe the shadow fading. Let

$$R(i,x)[\text{mW}] = 10^{RSRP(i,x)/10}, \tag{2}$$

where $R$ is the RSRP in mW units.

Doppler shift is another important feature we should consider for high speed rail [22]. Doppler shift refers to the phenomenon observed in mobile communication, where the fast movement of the mobile station and the varying distance between the receiving terminal and the base station cause the synthesized frequency to fluctuate both above and below

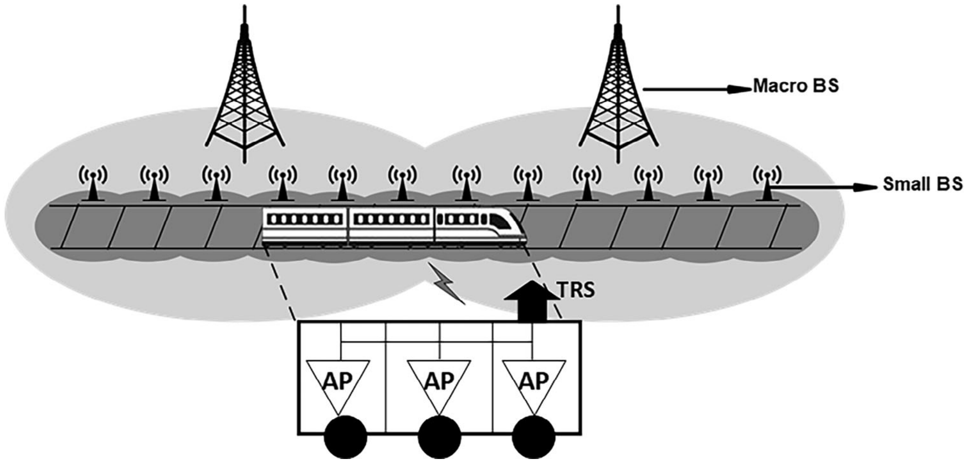


**FIGURE 1** System architecture.

the center frequency [23]. The Doppler shift will result in inter-carrier interference (ICI) which will decrease the received power. Thus, the RSRP with the normalized noise power at the time $t$ and position $x$ from the $i$-th BS can be modified as

$$RSRP(i,x)[\text{dBm}] = 10\log_{10}\left[\frac{R(i,x)}{R(i,x) * \Delta + 1}\right], \tag{3}$$

where $\Delta = \int_{-1}^{1}(1-|x|)\left(1-J_0\left(2\pi f_d T_s x\right)\right)dx$ is the ICI power and details can be found in [24–26]. $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind, $f_d$ represents the maximum Doppler frequency shift and $T_s$ is the symbol duration.

Pass loss models are different for macro BSs and small BSs. The COST 231 Hata model for macro BS is proposed in [27], which is applicable to HSR scenario. The simplicity and availability of accurate factors make this model widely used for radio propagation in the urban, suburban and rural areas for HSR system.

The path loss model in the $i$-th small BS can be represented as

$$PL(i,d_i)[\text{dB}] = PL(d_0) + 10\theta\log(d_i), \tag{4}$$

where $d_i$ is the distance between the $i$-th small BS and the mobile train, $\theta$ is the path loss exponent for the mmWave frequency band, and $PL(d_0) = 10\theta\log(4\pi d_0/\lambda)^2$, $\lambda$ is the wave length. Path loss depends on the distance between the transmitter and receiver.

For macro BS, we consider the inter-cell interference caused by the nearest neighboring base stations with same frequency and can be denoted as

$$I_m[mW] = \sum_{n_m=1, n_m\neq m}^{N_{nei.m}} 10^{RSRP(n_m,x)/10}, m \in M, \tag{5}$$

where $M = \{m_1, m_2, m_3 \dots m_f\}$, $f$ is the number of macro BS and $N_{nei.m}$ is the number of the nearest neighboring macro BS. $RSRP(n_m, x)$ obtained from (3) is the received interference signal power from the co-channel macro BS.

Similarly, the interference power received from the nearest neighboring small BSs can be expressed as

$$I_s[mW] = \sum_{n_s=1, n_s\neq s}^{N_{nei.s}} 10^{RSRP(n_s,x)/10}, s \in S, \tag{6}$$

where $S = \{s_1, s_2, s_3 \dots s_p\}$, $p$ is the number of small BS and $N_{nei.s}$ is the number of the nearest neighboring small BS. $RSRP(n_s, x)$ obtained from (3) is the received interference signal power from the co-channel small BS.

Therefore, at location $x$, we can express SINR from the $i_m$-th macro BS and the $i_s$-th small BS, respectively, as follows:

$$SINR_{i_m}[dB] = 10\log\left[\frac{10^{RSRP(i_m,x)/10}}{I_{i_m} + N_0}\right], \tag{7}$$

$$SINR_{i_s}[dB] = 10\log\left[\frac{10^{RSRP(i_s,x)/10}}{I_{i_s} + N_0}\right], \tag{8}$$

where $N_0$ is the noise power, $RSRP(i_m, x)$ and $RSRP(i_s, x)$ obtained from (3) is the received signal power from the macro and the small BS, respectively.

## 3 | BACKGROUND OF SUPPORT VECTOR MACHINE

This section provides a brief introduction to the SVM algorithm. SVM is a popular algorithm in supervised learning, commonly employed for both classification and regression tasks. However, its predominant usage lies in classification problems. In addition, SVM is not limited to linear classification tasks, it can also effectively handle non-linear classification through the use of the kernel trick. By doing so, SVM can implicitly map the inputs into high-dimensional feature spaces, thereby enabling efficient non-linear classification. The main

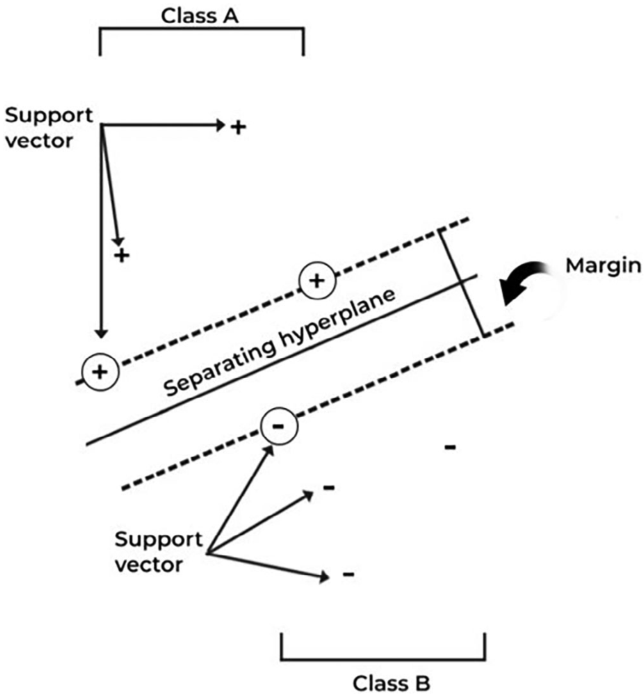


**FIGURE 2** SVM optimizes margin between classes or support vectors [28].

objective of the SVM algorithm is to construct an optimal line or decision boundary, known as a hyperplane, capable of effectively separating different classes within an n-dimensional space. This facilitates accurate categorization of future data points into their appropriate categories.

SVM identifies crucial points or vectors, known as support vectors, which play a vital role in defining the hyperplane. Support vectors are data points that are closer to the hyperplane and significantly impact its position and orientation. By leveraging these support vectors, we aim to maximize the margin of the classifier. A margin is a separation gap between the two lines on the closest data points. It is calculated as the distance from the hyperplane to support vectors. The relationship between hyperplane, support vectors and margin is shown in Figure 2.

The basic principle of SVM is to find a decision hyperplane among linearly separable set. The expression of the hyperplane can be shown as follows:

$$f(\mathbf{x}) = \langle \boldsymbol{\omega}, \mathbf{x} \rangle + b, \tag{9}$$

where $\mathbf{x}$ is the feature input, $\boldsymbol{\omega}$ is the weight matrix and $b$ is a bias term.

The cost function is given by the following formula:

$$J = \min \frac{1}{2} \|\boldsymbol{\omega}\|^2 + C \sum_{i=1}^{N} \mu_i, \tag{10}$$

where $\mu_i \geq 0$ and $\|\boldsymbol{\omega}\|^2$ is the Euclidean distance from the original to the hyperplane. Moreover, $N$ is the number of training set, $C$ is a parameter for regularization which can be used to control the number of errors that is permitted on the training dataset.

The prediction model in Equation (9) can be expressed as a linear combination of the training data $\mathbf{x}_i$ [29]. It can be represented as follows:

$$f(\mathbf{x}) = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) K\left(\mathbf{x}_i, \mathbf{x}_j\right) + b, \tag{11}$$

where $\alpha_i, \alpha_i^* \in [0, C]$ and $K\left(\mathbf{x}_i, \mathbf{x}_j\right)$ is the kernel function. In this paper, we utilize the radial basis function (RBF) as the kernel function:

$$K\left(\mathbf{x}_i, \mathbf{x}_j\right) = exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right), \tag{12}$$

where $\sigma$ is the Gaussian kernel width. It implicitly determines the data's distribution after being mapped to the new feature space. $\|\mathbf{x}_i - \mathbf{x}_j\|^2$ represents the squared Euclidean distance between vectors $\mathbf{x}_i$ and $\mathbf{x}_j$ in the original feature space. An equivalent definition involves a parameter $\gamma = \frac{1}{2\sigma^2}$:

$$K(\mathbf{x}_i, \mathbf{x}_j) = exp\left(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2\right), \tag{13}$$

where $\gamma$ is the kernel coefficient for the kernel function. Essentially, the kernel function is a mathematical function that takes two input data points in the original feature space and computes their similarity or inner product in the transformed space [30]. It is particularly useful when dealing with non-linearly separable data in high-dimensional feature spaces. Thus, the kernel function enables the transformation of input data into a higher-dimensional space where it might become linearly separable. Mathematically, given two data points represented as vectors $\mathbf{x}_i$ and $\mathbf{x}_j$, the kernel function is denoted as $K(\mathbf{x}_i, \mathbf{x}_j)$. The kernel function can be thought of as a measure of how similar or related the data points are.

In other words, the kernel function can implicitly represent the high-dimensional feature space without explicitly computing the transformed data points.

## 4 | PROPOSED SVM-BASED HANDOVER ALGORITHM

In this section, the proposed SVM-based HO scheme is presented. Our focus is on supervised learning machine. This type of learning involves training the machine using a set of examples consisting of input–output pairs, also known as labeled samples. By analyzing the errors in its predictions, the algorithm refines the learning process. Subsequently, we evaluate the trained model's performance using the test set, to assess its ability to do predictions in the future.

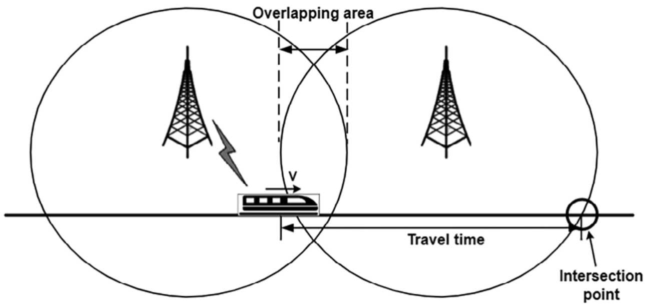


**FIGURE 3** Travel time diagram.

## 4.1 | Data preparation and process

We jointly consider three major criteria for the HO decision making process, that is, RSRP, SINR and travel time ($T$).

### 4.1.1 | RSRP

RSRP refers to reference signal receive power and measures the power of the reference signal received at the antenna of the mobile device. It provides an indication of the radio link quality between the mobile device and the serving cell.

### 4.1.2 | SINR

SINR often serves as an indicator of the interference level on the radio link and evaluates the connection's overall quality. In the proposed scheme, this parameter helps to select a BS that can provide higher SINR value, that in turns decreases the HO failure rate.

### 4.1.3 | Travel time

The travel time ($T$) refers to the duration it takes for a train to travel from its current position to the point where it exits the coverage area of a BS. In other words, it is the time that the train takes to reach the point where the railway track intersects with the boundary of the BS coverage area, as depicted in Figure 3. This metric is utilized to reduce the HO number.

In Figure 3, we assume that the circle drawn is the communication range that a BS can cover.

A multiple criteria matrix is formed and can be used as model input to predict an optimal BS for HO. The dataset can be denoted in the Equation (14), where $m$ is the number of samples, $X_m$ means the inputs of the sample $m$ and $y_m$ stands for the outputs of the sample $m$ as well as the different classes in the SVM algorithm.

$$D = \{(X_1, y_1), (X_2, y_2), \dots, (X_m, y_m)\}. \tag{14}$$

For our scenario, the inputs contain features including the RSRP, SINR, and $T$ in the network. Furthermore, in addition to an input matrix $X$, the corresponding output matrix $y$ is also generated and the elements in matrix $y$ are the chosen BS index for each sample (each waypoint). Here, we use index $p_i$={1,2,3,4,5} to describe the 5 different classes in the output matrix which are the next 5 neighboring BSs including one macro BS and four small BSs for each sample. For the generation of the output matrix, we use Multiple Criteria Decision Making technique (MCDM) method [31] to select the optimal BS and it ranks the 5 candidate BSs (5 classes) for each sample which is to calculate weighted network priority described as an overall value $Z$. In order to select the optimum BS of them for each sample, the BS index with the highest $Z$ will be picked as the output of each sample. $Z$ can be calculated by the following formula,

$$Z = \omega 1 * RSRP + \omega 2 * SINR + \omega 3 * T, \tag{15}$$

where $\omega 1, \omega 2$ and $\omega 3$ represent the weights for the RSRP, SINR, and $T$, respectively. In addition, their range is from [0,1] and $\omega 1 + \omega 2 + \omega 3 = 1$. More specifically, there are 5 classes (5 candidate BSs) to be selected in our model. In terms of the dataset, it includes the input and the output of each sample which are different features and the selected BS index for each sample based on MCDM method.

The selection of weights has a crucial impact on selecting the candidate BS as the output of each sample. The application of the MCDM method in BS selection relies on the approach used to calculate the weighted network priority criteria. Thus, in this paper, we adopt the standard deviation method [32] to calculate the weight of each individual criterion as shown in the following equations,

$$\delta_k = \sqrt{\frac{1}{m} \sum_{j=1}^{m} \left(\alpha_{jk} - H_k\right)^2}, \tag{16}$$

where $m$ is the number of candidate alternatives and $k = 1, 2, \dots, s$ and $s$ is the number of criteria. Further, $H_k = \sum_{j=1}^{m} \alpha_{jk} / m$ means the average score. Then, we can obtain the objective weight $\varphi_k$ of $k$-th criteria which can be denoted as follows,

$$\varphi_k = \frac{\delta_k}{\sum_{k=1}^{s} \delta_k}. \tag{17}$$

If the SD value is larger, the criteria should be given an important weight value having more effect on decision making.

## 4.2 | The SVM-based predictive handover scheme

The proposed SVM-based handover prediction method to improve mobility management is presented in this section. In this work, handover prediction is considered as a classification problem. The proposed HO scheme is summarized in Algorithm 1.

**ALGORITHM 1** Proposed HO algorithm

1: ***Initialization***:

2: ***Input***: Dataset

3: ***Output***: Target BS

4: Dataset are preprocessed to extract the various features such as RSRP, SINR and time $T$

5: The dataset is divided into training set (80%) and testing set (20%)

6: SVM takes these features as input. Then, SVM classifier is used to choose the best BS based on the values of the criteria. (Refer to Figure 4)

7: ***End***

The overall scheme comprises two phases: the training phase and the prediction phase. In the training phase, the input to the model is the generated dataset including the different features along with the whole railway track and their labeled next selected BS index $\{p_i\}$. Here, $\{p_i\}$ is the corresponding class in which the learning algorithm aims to match the input features of each sample. After the training phase, the prediction phase is to apply the trained classified model in the decision making process to predict the next BS based on future input features. From step 4 to step 5, they are the data preparation process. Step 6, includes the training process first and then the prediction process using the trained classifier. Moreover, the prediction phase can occur in real time, especially in the HO decision making process requiring immediate responses. However, the training phase involves extensive computation and data processing based on the available information in the network. Thus it is typically conducted offline rather than in real-time. More specifically, during the training phase, the model learns patterns and relationships in labeled training data. This process requires significant computational resources and time because the model continuously adjusts parameters to minimize the loss function of the training data. Once training is completed, a trained model is generated, which can be used for subsequent prediction phases. In addition, the SVM classification model was trained using the 'fitcecoc' function, which employs a class error-correcting output codes approach. This function provides a fully trained multi-class error-correcting output model. By utilizing the One-vs-One coding design, 'fitcecoc' creates K(K-1)/2 binary SVM models, where K represents the number of unique class labels. The implementation of error-correcting output codes and the one-vs-one coding design in SVM enhances the performance of the classification model [33].

Thus, the flowchart of the proposed HO scheme can be illustrated in Figure 4.

The objective of the SVM is to find the decision boundary between different classes by constructing a hyperplane in a high-dimensional space [34]. This hyperplane is positioned to have the maximum distance from the nearest training samples of either class. Furthermore, the learning capability and accuracy of SVM according to the chosen parameters and the kernel function applied. The selection of an appropriate kernel function significantly impacts the performance of SVM [35, 36]. In our experiments, four kernels are used: linear, polynomial, sigmoid

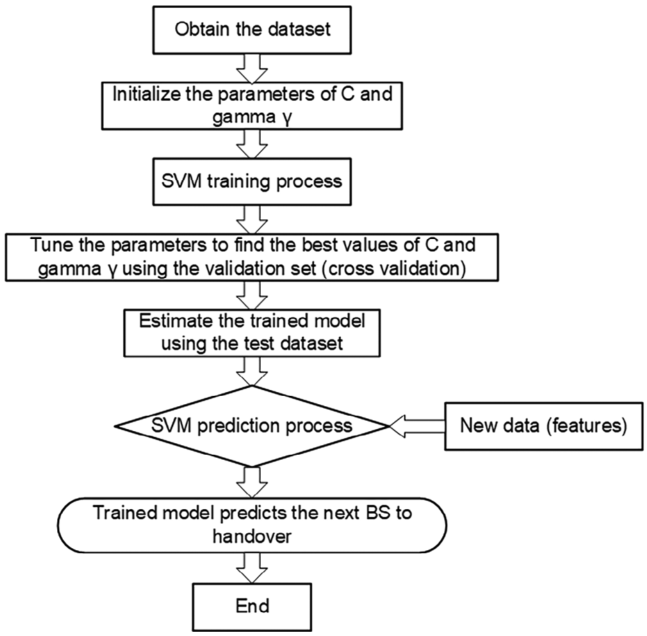


**FIGURE 4** The SVM algorithm for HO situation.

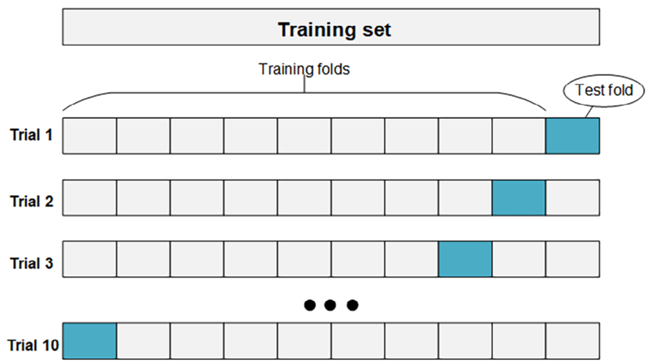


**FIGURE 5** K-fold cross-validation for $K$=10.

and RBF. We found that the RBF kernel can achieve the highest accuracy, which maps sample vectors into a higher dimensional space. The RBF kernel parameter $\gamma$ and the SVM slack variable $C$ are optimized by using K-fold cross-validation [16] on a subset of the training set which is described in Figure 5. This enables us to determine the most suitable values for $\gamma$ and C that maximize the performance of SVM.

In this approach, the training set is divided into $k$ parts. Then, the learning process involving $k$ trials will be performed. During each trial, one of the $k$ parts is designated as the test set which is named as the validation set, while the remaining $k$-1 parts are utilized for training. Finally, the model structure that achieves the highest average score on the validation sets across the $k$ trials is selected. It is particularly helpful when dealing with limited data to avoid overfitting, which occurs when a model performs well on the training data but struggles to work well on new or unseen data.

In the proposed scheme, the significant steps are the creation of the dataset and the training procedure. Once the trained

SVM model is obtained, it can be promptly used in the decision making process to determine the next target BS to handover.

## 5 | RESULTS AND DISCUSSION

This section evaluates the performance of the proposed SVM based HO scheme.

### 5.1 | Experiment setup

In order to evaluate the handover performance of the proposed algorithm in the HSR system, we firstly set up a HSR communication network model in MATLAB. In this model, we assume that the overall length of the railway track is 15 km and the network consists of 4 macro BSs and 77 small cells, which are distributed linearly along one side of the track as shown in Figure 1. Additionally, we assume that the bandwidth resources of both macro and small BSs are sufficient for user data. Based on this setup, the bandwidth of small BS will not be fully occupied and may only use a small part of the bandwidth depending on the number of active users as in the situation when more trains and users are considered, dynamic data offloading to small cells are also needed to avoid congested data traffic in macro BSs. According to analysis in Section 4, we build a trained classification model during the training phase in the SVM algorithm. After the training phase, the model we obtained can be used to predict (classify) the next BS in HO decision making. Here, we have five different classes (5 neighboring BSs) for the train to handover at position $x$.

In addition, we collect a dataset of size 5000 samples in this scenario, from which 4000 are used for training purpose (80%), and 1000 samples for test purpose (20%).

### 5.2 | Simulation results of handover performance

The performance of the proposed HO scheme is evaluated in terms of the average number of HOs, HO failure probability and user mean throughput.

- Handover failure probability:

  This metric is used to quantify the likelihood of an unsuccessful handover. Handover failure occurs when the handover trigger condition is met but the received power from the target BS is lower than a threshold $\beta$ which is the minimum received signal strength (RSS) to maintain a wireless communication link. Thus, the handover failure probability at position $x$ can be expressed as

$$\begin{aligned} P_{fail}(x) &= \Pr\left\{R_t(x) < \beta \mid R_t(x) - R_s(x) > H\right\} \\ &= \frac{\Pr\left\{R_t(x) < \beta, R_t(x) - R_s(x) > H\right\}}{\Pr\left\{R_t(x) - R_s(x) > H\right\}}, \end{aligned} \tag{18}$$

  where $R_t$ is received signal power from the target BS and $R_s$ is received signal power from the serving BS. In addition, $\beta$ is signal threshold and $H$ is the hysteresis. The system's performance decreases as the probability of HO failure increases, which can lead to signal loss and interruptions in an active data session.

- Throughput:

  It refers to the effective data rate of a network. It measures how much data can be transmitted from one point to another in a specific amount of time (usually measured in seconds). The throughput can be expressed as:

$$\text{Throughput} = B * \log 2(1 + SINR)(\text{ bit/s}), \tag{19}$$

  where $B$ is the bandwidth of the channel. Because SINR is one of the criteria we used, selected BS can provide better SINR, which improves the throughput.

**TABLE 1** Simulation parameters.

| Parameters | Value |
|---|---|
| Bandwidth ($B$) | $B_{macro} = 20$ MHz |
| | $B_{small} = 500$ MHz |
| Carrier frequency ($F$) | $F_{macro} = 2$ GHz |
| | $F_{small} = 28$ GHz |
| Transmit power ($P_t$) | $P_{t_{macro}} = 46$ dBm |
| | $P_{t_{small}} = 23$ dBm |
| Number of BS ($N$) | $N_{macro} = 4$ |
| | $N_{small} = 77$ |
| Noise power spectral density | −174 dBm/Hz |
| Distance from BS to rail ($D$) | $D_{macro} = 100$ m |
| | $D_{small} = 2$ m |
| Height of BSs($h$) | $h_{macro} = 30$ m |
| | $h_{small} = 7$ m |
| Height of train($h_{train}$) | $h_{train} = 1.5$ m |
| Shadowing standard deviation ($SD$) | $SD_{macro} = 4$ dB |
| | $SD_{small} = 8$ dB |

The parameters used in the simulation are listed in Table 1.

In Figure 6, it depicts that there is an increasing number of HOs with the increase of train speed. We compare the average number of HOs of the proposed scheme with the conventional HO approach, the existing algorithm [37] and other classification algorithms which are Decision Tree (DT), K-Nearest Neighbors algorithm (KNN) and Artificial Neural Network algorithm (ANN). The conventional HO method is A3 event and we use its performance as the benchmark. From the figure, it's obvious that the proposed method outperforms the existing algorithms as well as the conventional method and achieves the lowest HO number. Furthermore, among various classification algorithms, ANN performs better than KNN and DT because of its multi-layer connection and various activation functions to deal with nonlinear classification problems.

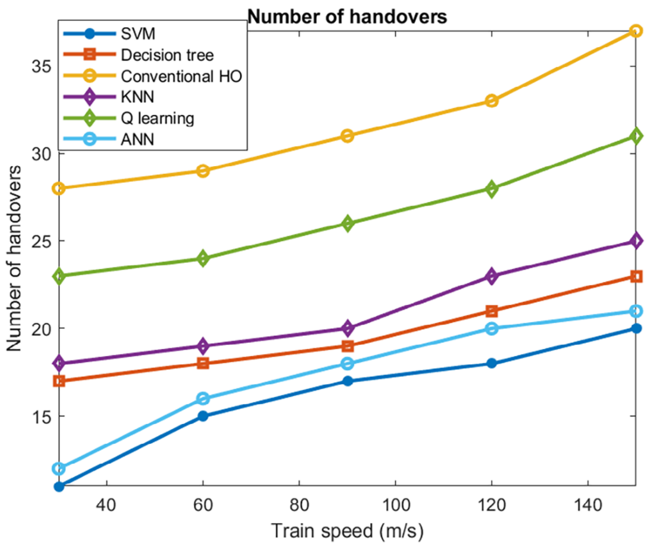


**FIGURE 6** Average number of HOs.

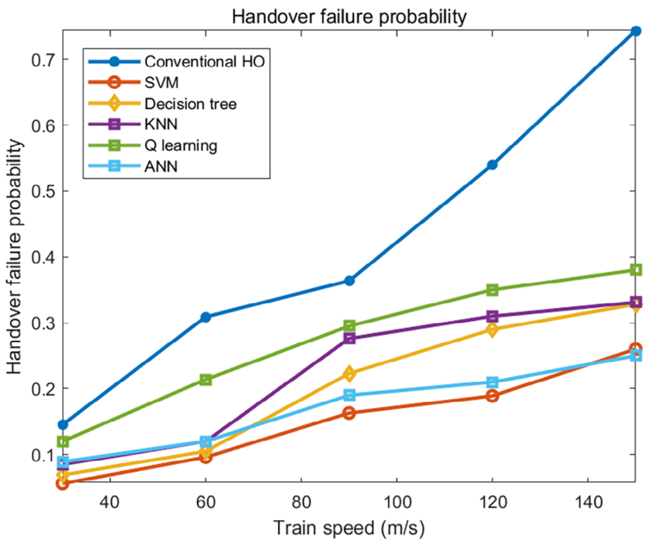


**FIGURE 7** Handover failure probability.

Therefore, the simulation result clearly indicates that the SVM-based HO method is significantly effective in reducing the number of unnecessary HOs.

The probability of HO failure rises with the faster speed of the train which is shown in Figure 7. This is primarily due to the limited time available for the BSs to execute the handover process at the target cell and also the degraded signal. The proposed scheme achieves the best performance when compared with the conventional HO method and the existing HO algorithm [37]. Initially, the HO failure rate is almost same for the proposed scheme and other classification learning algorithms. However, when the train speed exceeds 60m/s, the proposed SVM-based HO method performs better than other learning algorithms. Thus, the proposed method outperforms in terms of handover failure probability.

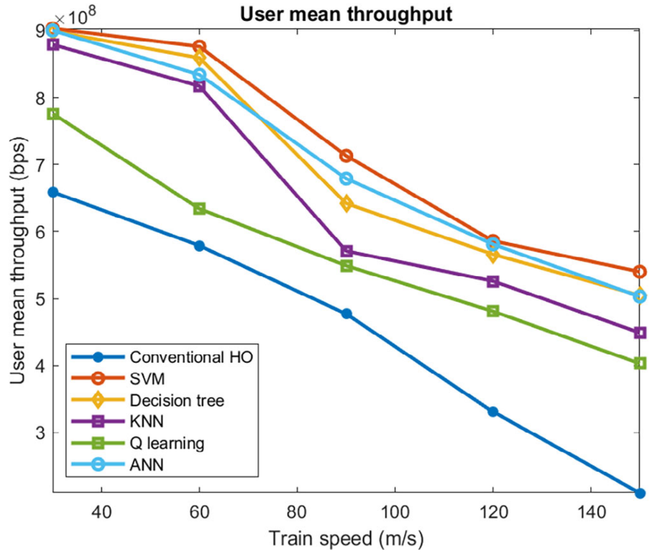


**FIGURE 8** User mean throughput.

**TABLE 2** Performance metrics obtained on the test set of dataset.

| Algorithm | Accuracy | Precision | Recall | F1 score |
|---|---|---|---|---|
| Support vector machine | 98.4% | 0.882 | 0.897 | 0.89 |
| Decision tree | 95.6% | 0.91 | 0.906 | 0.9 |
| K-nearest neighbors | 93.3% | 0.94 | 0.76 | 0.84 |
| Artificial neural network | 99% | 0.86 | 0.984 | 0.92 |

With the increase of train speed, the throughput of users for all methods is decreased as illustrated in Figure 8. Conventional HO method has the worst throughput performance due to the high HO failure rate and the big number of HOs. In addition, the proposed scheme clearly outperforms the existing algorithm [37] in the literature. When compared with other classification learning algorithms, the proposed method and ANN algorithm can achieve slightly better throughput than DT and obviously better throughput than KNN algorithm. Specifically, when the speed of train is 90m/s, the throughput of the proposed scheme outperforms by about 5%, 11.1%, 24.9%, 29.8% and 49.5%, respectively, in comparison to ANN, DT, KNN, Q-learning algorithm and conventional HO scheme. The increased number of HO can reduce the throughput. Since frequent handovers can lead to temporary disruptions (handover time) in data transmission. Each handover process involves control signaling and potential latency, which can lower the effective desired data throughput. Moreover, high handover failure probability can also increase data transmission interruptions, thus negatively impacting throughput.

## 5.3 | Performance analysis of classification algorithms

The performance of the proposed SVM-based HO algorithm, DT, KNN and ANN are evaluated by using different metrics

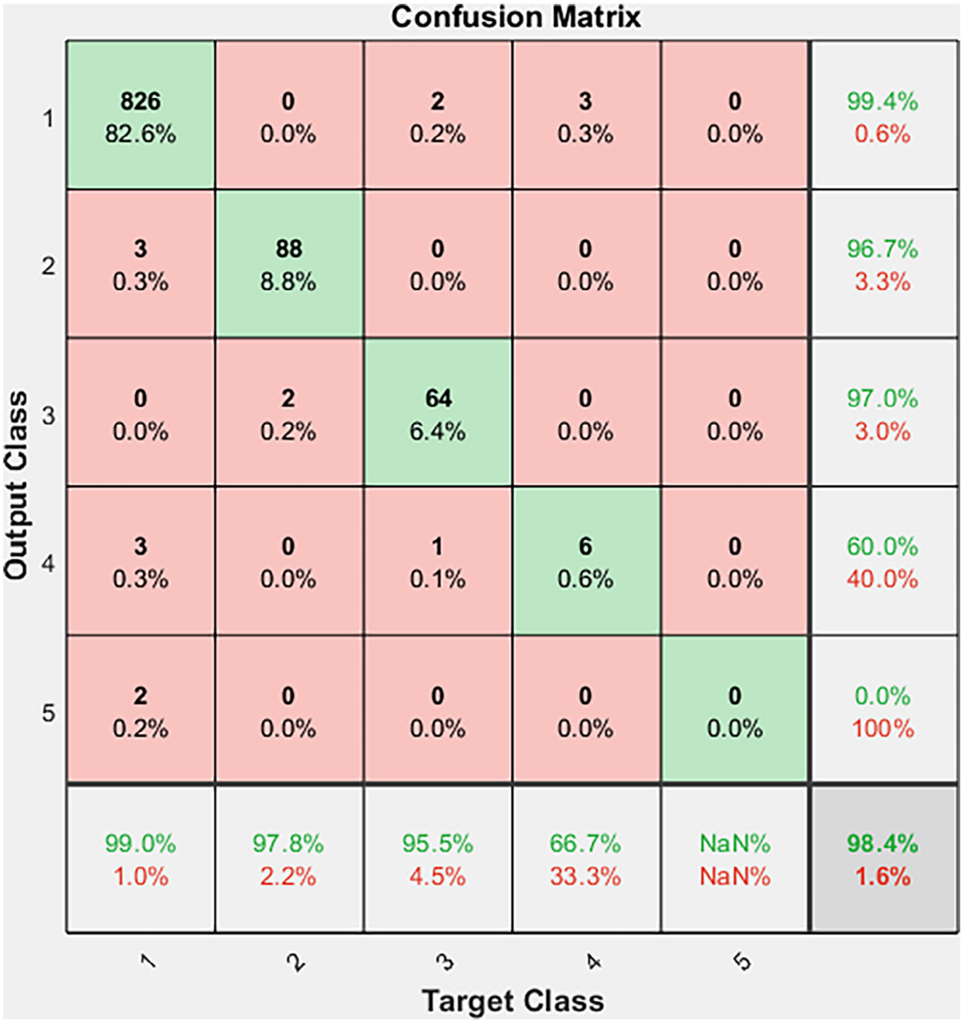


**FIGURE 9** SVM-based handover algorithm.

such as Precision, Recall, accuracy and F1 score. The performance metrics obtained during the test phase are summarized in Table 2.

The trained model is assessed on the test set of the dataset. Table 2 shows that SVM and ANN-based ML methods can achieve better accuracy and outperform in general when compared with other ML classification methods.

### 5.3.1 | Accuracy

The accuracy of classification is defined as,

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}. \tag{20}$$

Accuracy is the ratio of the total number of correct predictions and the total number of predictions. It is used to evaluate the accuracy of the whole prediction model.

### 5.3.2 | F1 score

The F1 score is a metric that combines precision and recall through a harmonic mean. A higher F1 score, closer to 1, indicates better performance of the ML algorithm. It can be defined as follows,

$$\text{F1 score} = 2 * \frac{(\text{precision} * \text{recall})}{(\text{precision} + \text{recall})}, \tag{21}$$

where,

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{22}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{23}$$

where TP, TN, FP and FN mean true positives, true negatives, false positives, and false negatives, respectively. Precision is the ratio of the True Positives to all the Positives and also gives us a measure of the relevant data points. But for the Recall, it is the measure of how accurately our model is able to classify the

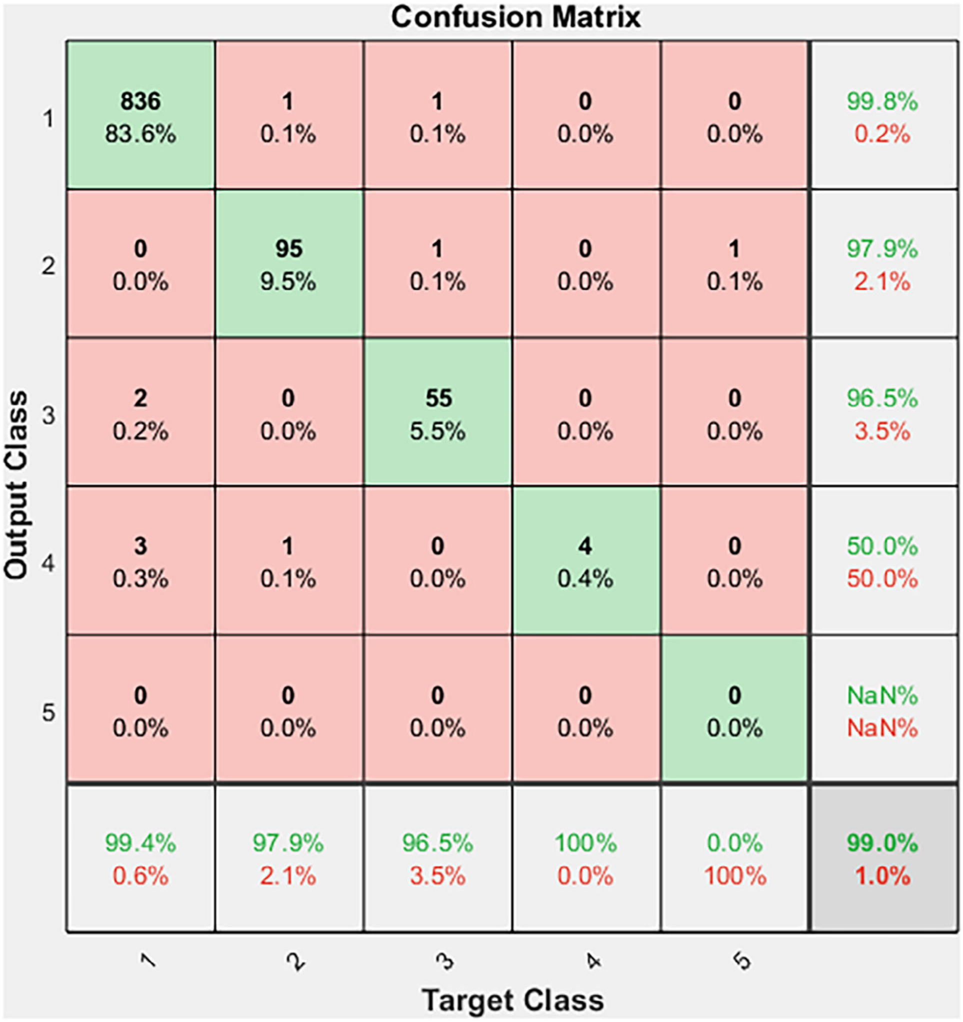


**FIGURE 10** ANN-based handover algorithm.

relevant data. Therefore, F1 scores strike a trade-off between precision and recall by computing the weighted average of the two measures to evaluate the classification model. From Table 2, we can conclude that F1 score for ANN performs slight better than other algorithms during the test phase.

Confusion matrix is often used to provide valuable insight into the accuracy of our predictions and their alignment with the actual values. It enables us to analyze the correctness of our predictions and evaluate their performance comprehensively. Correct prediction means the predicted class matches the actual class by the classification model. The results of the confusion matrix with the proposed SVM scheme are presented in Figure 9 and other ML-based algorithms are shown from Figures 10–12.

In Figure 9, the matrix compares the actual classes (target classes) with the predicted classes (output classes) by the classification model.

- **Green Blocks (Diagonal)**

  These represent correct predictions by the classification model, where the predicted class matches the actual class. They are often referred to as "True Positives" for the respective classes. For instance, the block with number 826 indicates that there are 826 samples where class 1 was correctly predicted as class 1.
- **Red Blocks (Off-Diagonal)**

  These indicate incorrect predictions. The red blocks not on the diagonal show samples where the prediction is different from the actual class. For example, the red block with number 2 in the first row and third column indicates that there are 2 samples where the actual class was 3, but the model incorrectly predicted it as class 1.
- **White Block(Right Side)**

  The percentages in the last column represent the precision for each class, including both the percentages of correct and incorrect predictions. For instance, for actual target class 1, 99.4% of the predictions were correct and 0.6% were incorrect.
- **White Block(Bottom)**

  The percentages in the bottom row represent the recall for each class. For example, 99.0% of the predictions for class 1 are actually class 1, but 1.0% are not.
- **Gray Block**

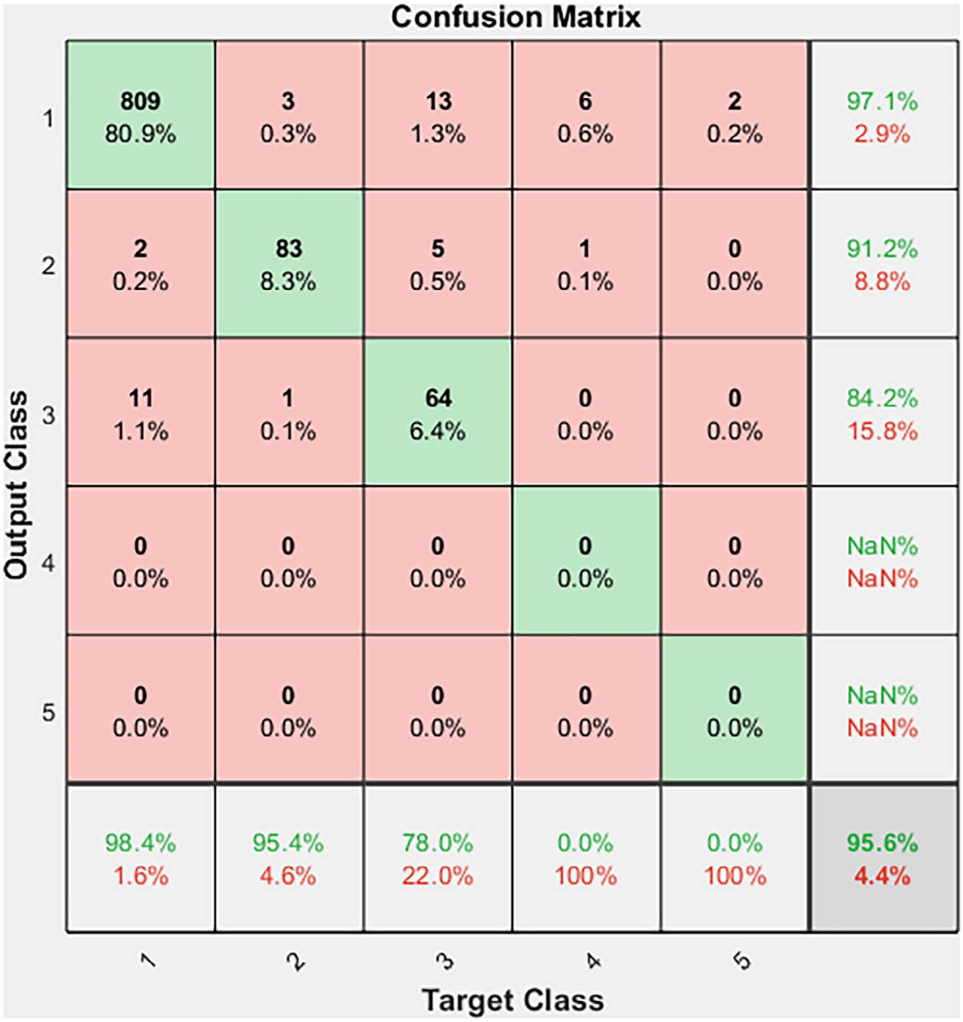


**FIGURE 11** DT based handover algorithm.

Overall Accuracy: this is the sum of the green block numbers divided by the total predictions. Accuracy should be as high as possible.

From Figures 9 and 10, the confusion matrix illustrates that the SVM and ANN algorithms have similar prediction performance and both achieve the highest accuracy of the model which are 98.4% and 99% accuracy, respectively, when compared to other ML algorithms of 95.6% and 93.3%.

### 5.3.3 | Computational complexity

The computational complexity analysis of the proposed algorithm also plays a vital role in the real time implementation. Thus we do a comparison in terms of complexity analysis of our proposed scheme and other algorithms as shown in Table 3.

It shows the computational complexity of the different algorithms used in the Big-O notation, where $n$ is the size of the training set, $f$ is the number of features, and $L$ is the number of layers for neural networks.

**TABLE 3** Computational complexity of different algorithms.

| Algorithms | Training |
|---|---|
| Support vector machine | $O\left(n^2 f + n^3\right)$ |
| Decision tree | $O\left(n^2 f\right)$ |
| K-nearest neighbor | $O\left(nf\right)$ |
| Artificial neural network | $O\left(n^5 fL\right)$ |

From Table 3, it is observed that the complexity of the KNN is smallest compared to other ML methods due to the underlying algorithms of these machine learning models. For KNN, it is a lazy learning algorithm that stores all training data points and makes predictions based on the nearest neighbors of a given data point. Thus, the computational complexity for KNN is relatively simple. In our proposed scheme, SVM-based handover algorithm is a powerful algorithm for classification tasks, but it involves complex mathematical optimization to find the optimal hyperplane that separates different classes. This optimization process can be computationally intensive, especially

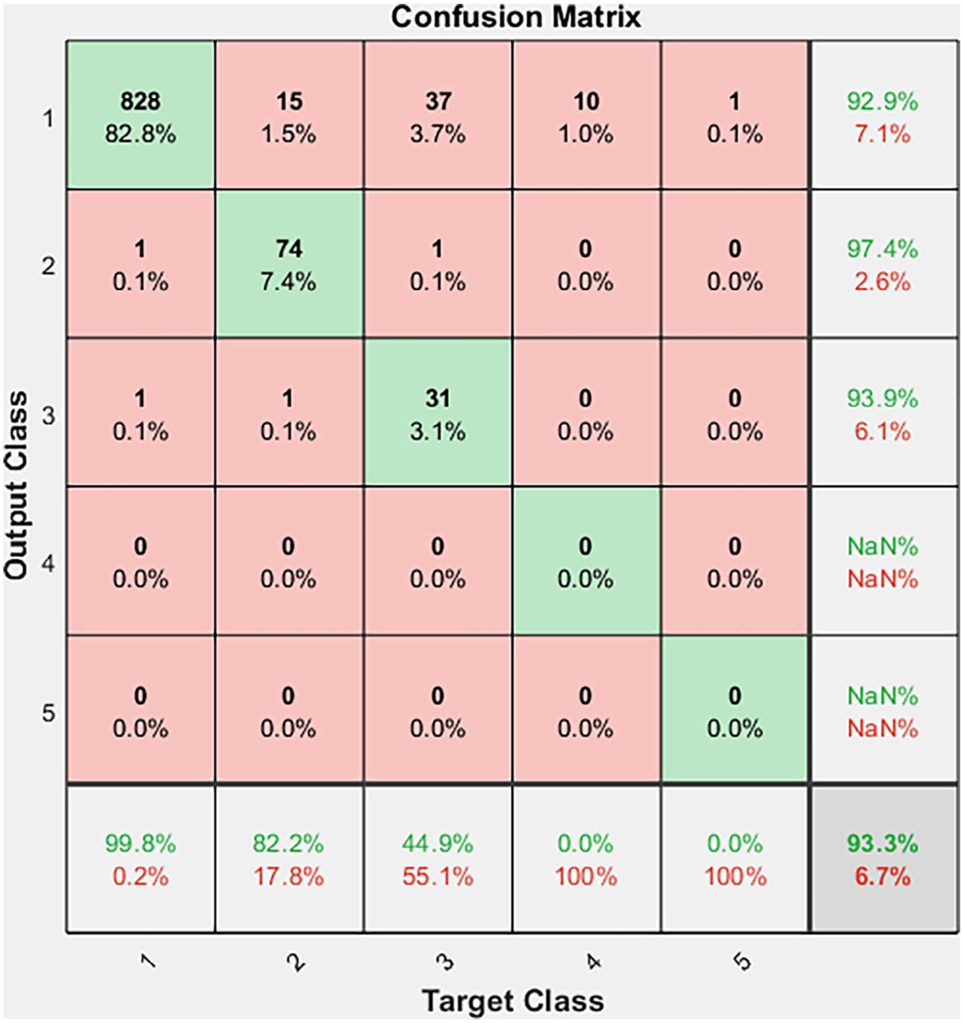


**FIGURE 12** KNN-based handover algorithm.

for large datasets or high-dimensional data. As a result, the complexity for SVM is larger compared to decision tree and KNN. However, based on the evaluation of the handover performance during decision making, SVM-based handover algorithm outperformed other algorithms in terms of the average number of HOs, HO failure probability and user mean throughput.

## 6 | CONCLUSION

This paper has investigated the HO problems in HSR wireless communication system. We propose a novel HO scheme based on SVM algorithm to predict the train's next target BS. Here, we approach the prediction task as a classification problem by applying the SVM on available information in HSR network. This paper establishes an effective SVM classifier model for optimal HO decision making by considering multiple criteria along the railway track. As demonstrated by the simulation results, the proposed scheme outperforms the conventional approach, existing algorithm [37] and other ML-based algorithms in terms of HO number, user mean throughput and HO failure probability. In addition, we also use various performance metrics to evaluate their accuracy. The results show that the SVM and ANN algorithms can achieve higher accuracy which are found to be 98.4% and 99%. However, during the actual implementation process (HO decision making process), the SVM can perform better in terms of the average number of HOs, HO failure probability and user mean throughput. Therefore, the proposed prediction framework holds great promise and deserves further investigation in real-world scenarios.

## AUTHOR CONTRIBUTIONS

**Siling Wang**: Conceptualization; data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Li Zhang**: Project administration; supervision; writing—review and editing.

## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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