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Adaptive Learning Techniques for Landslide Forecasting and the Validation in a Real World Deployment

Hemalatha T, Maneesha Vinodini Ramesh and Venkat P Rangan

Abstract

A forecasting algorithm using Support Vector Regression (SVR) used to forecast potential landslides in Munnar region of Western Ghats, India (10.0892 N, 77.0597 E) is presented in this paper. Forecasting for the possibility of landslide is accomplished by forecasting the pore-water pressure (PWP) 24 hours ahead of time, at different locations and across soil layers under the ground at varying depths, and computing Factor of Safety (FoS) of the slope. It is done by learning from the real-time sensor data gathered from Amrita University's Wireless Sensor Network (WSN) system deployed in Western Ghats for monitoring and early warning of landslides. We use two variations of SVR, SVR-Historic and SVR-Adaptive. SVR-Historic algorithm is trained with the data from July 2011 to December 2015 and tested for the period from January to November 2016. SVR-Adaptive algorithm is adaptively trained from July-2011 onwards and tested for the period from January to November 2016. PWP and the computed FoS from both the algorithms are compared with the actual PWP and FoS data and the Mean Square Error (MSE) for the SVR-Historic model is found to be 48.726 and 0.002 whereas the MSE for SVR-Adaptive model is found to be 12.438 and 0.0007 respectively. The PWP and the computed FoS from both the algorithms are tested for correlation using Pearson's correlation test, with 95% confidence interval and the coefficients for PWP is found to be 0.804 and 0.959 respectively with p-value of 2.2e-16, whereas for FoS it is 0.802 and 0.955 with p-value of 2.2e-16. The confidence intervals for PWP and FoS from both the models is 0.763 to 0.839 and 0.950 to 0.969 respectively. Among the two forecasting models, SVR-Adaptive model performs better with a low MSE of 12.438 and 0.0007 in forecasting PWP and the computed FoS values respectively and correlates with the real-time data ~ 95 % of the times. Application of this forecasting algorithm in real-world can thus provide 24 hours extra time for early warning which is a boon for government and public to prepare for landslides after early warnings.

Keywords

Learning techniques, Support vector regression, Forecasting methods, Early warning system

Introduction

In the pursuit of forecasting potential landslides and other natural disasters, government and other research organizations all over the world have gathered humungous amount of data by virtue of different technology such as remote sensing, synthetic aperture radar, wireless sensor networks, etc. Even though a lot of forecasting systems are developed using this massive data gathered, providing sufficient early warnings for landslides is still a challenge. In the context of forecasting and early warning for landslides, the techniques used are rainfall threshold based methods(Gabet,2004; Segoni, 2015), time series methods (Dore,2003; Loew,2015), Electrical Resistive Tomography based methods (Dostál,2014), Interferometric Synthetic Aperture Radar-based methods (Herrera,2009; Bozzano, 2011), infinite slope stability model based methods(Crozier, 1999; Chae, 2015), soil water index based methods etc (Brocca, 2012). Every method has its own advantages and limitations. Rainfall threshold based methods are well established and work well for a regional scale landslide alert and it has its own limitation for a site-specific alert. In the context of landslides, time series based methods are well established to forecast seasonal changes like monsoon precipitation and has its limitations if the data is discontinuous, non-stationary and if it has complex seasonal behavior. For instance, any real-time slope monitoring data will be discontinuous for several reasons and not seasonal necessarily. Also, most of the forecasting models are parametric in nature and makes strong assumptions about the data distribution and its underlying model

(Schmidt, 2008). In a real world scenario, the data recorded from a real-world process usually does not follow any standard distribution and hence a distribution-free learning needs to be done in order to discover the underlying hidden behavior of the real world process. The learning technique needs to make very few or no assumptions about the data, which is the drawback of the current learning techniques. Hence, non-parametric methods, which makes fewer or no assumptions about the data are more conducive to discover the underlying hidden behavior of the environment. Therefore, in this work, adaptive non-parametric methods are used. SVR-Historic and SVR-Adaptive are the two models presented in this paper. SVR-Historic model learns the PWP changes in the soil from the historic data to forecast the future PWP. SVR-Adaptive model learns the changes happening in the PWP of the soil from the historic data and real-time data and forecast the future PWP of the slope. With the onset of monsoon rainfall, dynamic changes in rainfall rate will trigger variability in soil properties at different heterogeneous soil layers, infiltration rate, pore pressure at different depths, groundwater table, etc. This variability in the environment and slope is captured by various sensors and the data streaming in real time is used for learning the variabilities happening in real-time in the environment. Among all these sensed information, the information about PWP at different soil layers is considered vital for the following four reasons: (1) PWP change happens slowly over time, whereas the parameters like displacement changes and crack occurrence are observed within a fraction of seconds at a later time. There is always enough time to early warn when the threshold limits of piezometer sensors are overcome; (2) the slope accounts for a slide when the soil loses its cohesion and PWP is indirectly proportional to soil cohesion; (3) piezometers deployed at different soil layers sense the PWP on these layers, and this information can be used for understanding the pressure gradient under the soil and localizing the vulnerable layers and slip surfaces.; (4) PWP at different location serves as input for the FoS calculations along with other soil and slope parameters. Therefore, it is highly necessary to understand PWP behavior with respect to rainfall and forecasting its value helps in forecasting the FoS of the slope ahead of time. Forecasting PWP and FoS 24 hours ahead provides 24 hours extra time for the government and public to prepare for landslides.

Study area and Amrita's WSN System

The study area is a small town ‘Munnar’ (10.0892 N, 77.0597 E) located in the landslide prone Western Ghats mountain region of Kerala in India. Rainfall varies from 3,500 – 5,500 mm every year with a maximum during the south-west monsoon months June, July & August respectively. The other monsoon is the North-east monsoon during the months of October, November and December. Idduki district, where Munnar is located is a landslide hotspot in the Western Ghats and every year landslides are very common during monsoon season, (Kuriakose,2009; Kuriakose,2010; Vijith,2008).

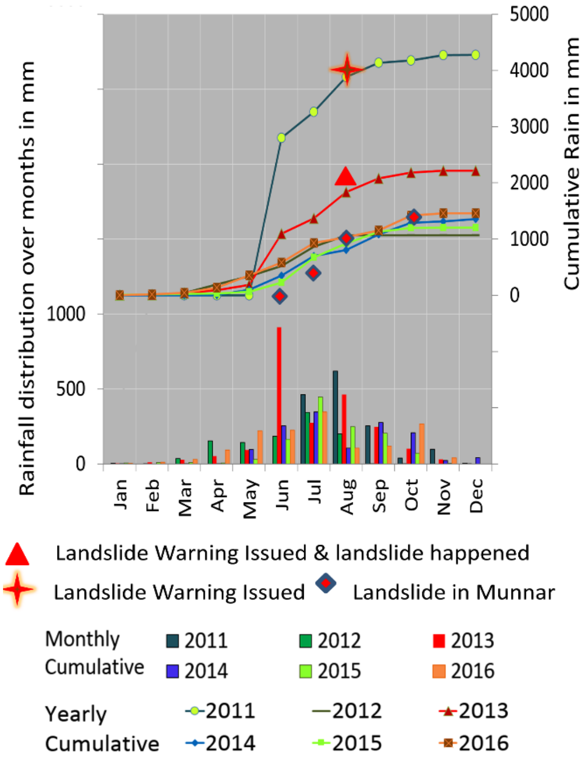

Fig. 1 Annual rainfall distribution and Cumulative rain over years from 2011-2016 in the deployment site Munnar. Legends are given for landslide warning issued and landslide happened in the deployment site. The other legend with ‘Landslide in Munnar’ corresponds to the landslides in the Munnar location far from the deployment site.

Amrita University’s WSN based landslide monitoring system is deployed in the town of Munnar (Ramesh, 2014; Ramesh, 2012), which is densely inhabited with shops, residents, schools and colleges. The study area has experienced two great historical landslides (Ramesh, 2014). The WSN based system is the world’s first comprehensive landslide monitoring and early warning system of its kind, consisting of heterogeneous sensors distributed spatially at different locations and across varying soil layers at different depths (Ramesh, 2014; US patent no:US8692668 B2). The heterogeneous sensors include meteorological sensors like rain gauge, geological sensors like moisture sensor, piezometer, vibration sensors like geophone and movement sensors like strain gauge, and tilt meter. These sensors sense the vital parameters like precipitation rate, soil moisture, PWP, ground vibration, slope movements respectively, and wirelessly transmit the data in real-time to the data management center in Amrita University. The deployment of the system started in 2006, and the data is been collected since 2009, the complete set of data for all sensors is available since 2011. Figure-1 shows the monthly rainfall distribution and cumulative rainfall distribution for the years 2011-2016, measured by the rain gauge in Munnar. The historical data and the real-time data are analyzed and early warnings are issued. The early warnings are issued at three levels, they are 'Early', 'Intermediate' and 'Imminent'. The forecasting techniques discussed in this paper, will provide 24 hours extra time for issuing the Intermediate level warning. So far the system has given three warnings, and they are in July-2009, August-2011 and August-2013. The time of warnings are highlighted in fig-1. Intermediate level warning was issued in July-2009 and early level warning was issued in August-2011 and both of them were conditional warnings for landslides with a higher rainfall rate for the next two days. There was little or no rainfall for the next two days after warnings, and naturally the slope rendered to stable conditions slowly. In August-2013, when the rainfall intensity crossed the threshold (Caine, 1980) the early level of warning for landslides was issued and landslides happened at several locations in and around Munnar. After the intermediate level warnings in August-2013, a landslide happened in the very near vicinity of 150 meters from the deployment site, which actually validated the successful working of our system. There was no death toll and no major economic loss happened during August-2013 landslide, since the public was prepared for landslides.

Real world data and the need for a distribution-free learning

To understand and model the behavior of PWP over time, we tried finding out the statistical distribution pattern of the data. We used six years of data of piezometer sensors from 2011 to 2016, since the sample size of our data is relatively high, we were able to easily reject well-known standard distributions. To visualize the distribution of piezometer sensor data with respect to other standard distributions we plotted the square of skewness vs kurtosis of the observed piezometer sensor data and all standard distributions. This plot is popularly known as Cullen and Frey graph and is shown in Fig-2. To account for the uncertainty of the estimated Kurtosis and Skewness of the PWP data 1000 bootstrap samples are drawn and compared with other standard distributions. The figure shows that the observed data do not follow any distribution. Therefore, in order to model the PWP behavior and variations under the soil, we preferred to use non-parametric methods, which do an assumption and distribution-free learning.

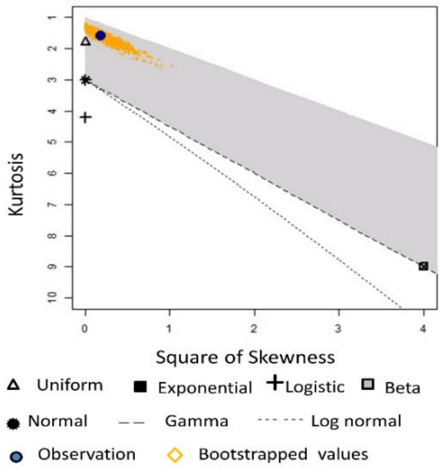

Fig. 2 Cullen & Frey graph to visualize the distribution of *PWP* data.

SVR for assumption free and distribution-free learning

Support Vector Regression is a non-parametric machine learning algorithm, which had proved to provide excellent results in many benchmark datasets (Russell, 2003); (Soman, 2009). SVR algorithm makes no assumption on the data and learns from the training data provided to it. The training data is created in such a manner, that it contains the relation between rainfall and PWP. The SVR formulation models the underlying relation as a regression function in the terms of kernel function and few other tuned parameters. The SVR formulation is discussed in detail in the sections below.

Relation between Rainfall and PWP

PWP variability at any layer of soil is predominantly because of two factors, they are the rainfall condition and ground water table. Rain is the primary known factor and ground water table is the secondary unknown factor. So we used rain conditions alone as the primary independent factor to determine the dependent factor PWP. Fig 3 shows the time series plot of the daily cumulative rain from July-2011 to November-2016 and the PWP variations from January-2011 to November-2016. Data from the piezometer at location 6 and 14 m (Ramesh, 2012) is used for analysis throughout this paper. Rain gauge deployment was completed in June-2011 and therefore we have the rain data from July-2011. From Fig-3, it can be seen that both PWP variation and rainfall data has peaks and valleys. Peaks are nothing but the instances where rainfall data and PWP variation are higher. Valleys are the instances when there is no rainfall or minimum PWP. Peaks and valleys of both the data do not occur at the same instant of time. There is a time lag between the peaks and valleys of rainfall data and PWP variation. This clearly indicates that after receiving ample amount of rainfall, there is a time lag for the PWP to build up.

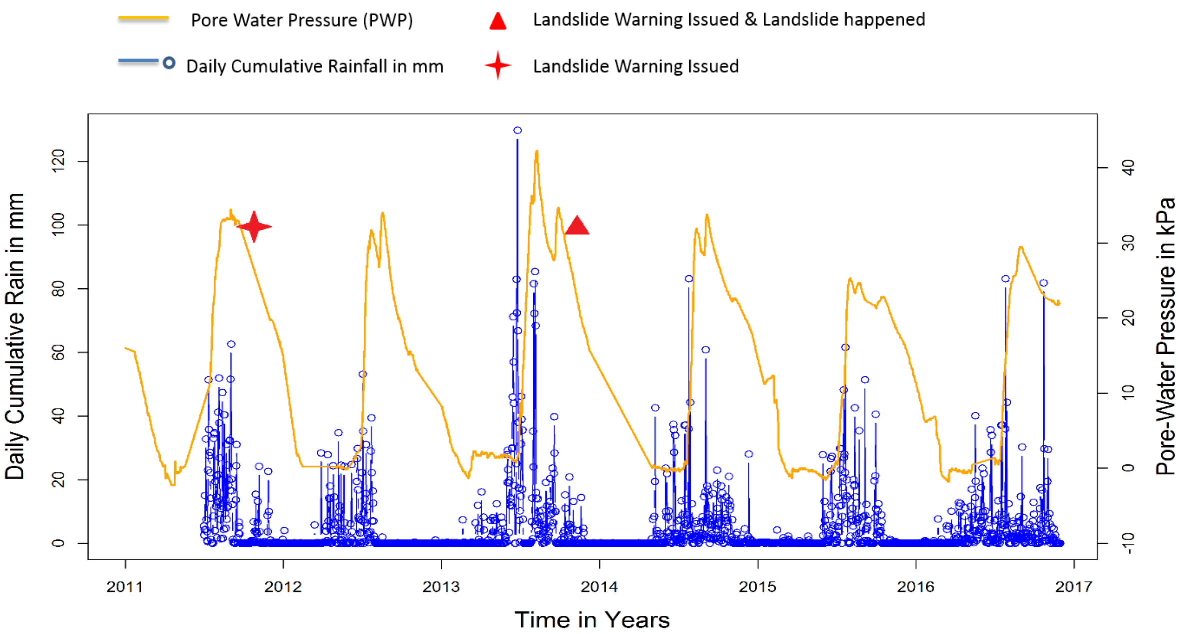

Fig.3 Plot of Daily cumulative rainfall and PWP at a depth of 14m in location L6 (Ramesh, 2012) from 2011-2016

In other words, the PWP is dependent upon the antecedent rainfall. The PWP values are at the minimum during the months of March, April and May. April and May being the pre-monsoon period, the PWP continues to be the same. This is because of two reasons, (1) maximum temperature is noticed during these months and there is very little or no rainfall, from January to March; (2) Because of high temperature and no rainfall, there will be less water between soil pores. With the start of pre-monsoon rains, the water percolates the soil pores and there is enough space between the pores for the water to percolate. Once when the soil pores are completely filled with water, the soil reaches its saturation state and pressure builds up in the pores suddenly due to increasing rainfall rate from monsoon rains. After heavy rainfall in June, the pressure in the soil pores starts increasing and reaches a maximum by the end of July and August. With the reduction in rainfall rate the pore-water pressure also gets reduced slowly. The decline of PWP starts from October and continues until March. Another inference from Fig-3 is that, there is very little or no rain during the months of December, January & February, but still there is significant PWP values. On the contrary, there are rain during the months of April, May and June, but the PWP values are significantly low. The above inference clearly indicates that, the PWP behavior is dependent on the previous months or antecedent rainfall. To forecast PWP, as a function of rain, the relation between antecedent rainfall conditions and PWP has to be learned initially. To accomplish that, we created linear models between different antecedent rainfall conditions AR_n and PWP. In AR_n, n refers to the 'number of days' of 'Antecedent Rainfall' AR . Antecedent rainfall conditions starting from 1 day to 180 days were calculated and linear models were created between different antecedent rainfall conditions. To evaluate the goodness of linear models, R-Squared correlation coefficient and Mean Square Error (MSE) are used as the metrics. The goodness of linear model results are shown in table-1 and figure-4. From table 1 and its corresponding plot in Fig-4, it is found that 130 days of antecedent rainfall has a higher R-Squared correlation of 0.71 with less mean square error of 39.02. Hence it can be interpreted that, 130 days of antecedent rainfall AR_{130} can better explain the PWP at that instant. For creating SVR models we have used PWP and AR_{130}.

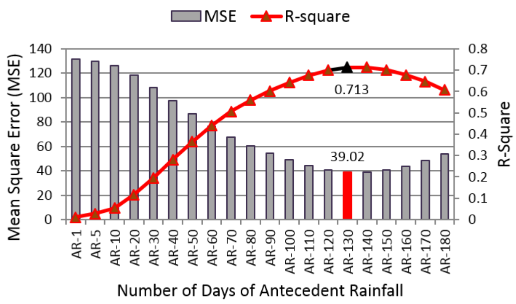

Fig.4 Plot of the goodness of linear model results

SVR formulation

C-SVR and Radial basis kernel function gives good results in modeling PWP variations compared to other SVR and kernel functions and so we have used the same for implementation in this paper. Radial basis function kernel for a multiple input training data is shown below.

$$\phi(x_i, x_j) = exp(-\sigma \| x_i - x_j \|^2) \quad [1]$$

where σ is a positive parameter, x_i, x_j are the input of the training data. Radial basis kernel maps the training data to an infinite dimensional space, therefore even the complex functions in the original input dimensional space become simpler in infinite dimensional space. The formulation of C-SVR, with ε insensitive loss function, is given below

$$Minimize$$

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*)$$

$$Subject to$$

$$y_i - \langle w^T \phi(x_i) \rangle - \gamma \le \varepsilon + \xi_i \quad [3]$$

$$\langle w^T \phi(x_i) \rangle + \gamma - y_i \le \varepsilon + \xi_i^*$$

$$\xi_i^*, \xi_i \ge 0,$$

Where,

w - weight vectors to be learned from the training data, y_i - output variable in the training data, i.e. PWP values that develop 24 hours later, γ - scalar quantity, generally known as a bias term, $\phi(x_i)$ - Radial basis kernel function of input training data, ε - small tolerable error, ξ_i and ξ_i^* - error values greater than ε, generally known as slack variables. The regression function learned from the above formulation is of the form $f(x) = w^T \phi(x) + \gamma$ [4].

A-insensitive loss function for an SV regression is that while learning the regression function $f(x)$ any error, less than ε from the actual target value (i.e.PWP) y_i is tolerated. Any error value greater than ε from the actual PWP value y_i is represented using slack variables ξ_i and ξ_i^*. In C-SVR, the amount of error that can be tolerated is decided while creating the model, and with respect to the model in this paper the value of ε is 0.01KPa. The objective of the above formulation in [3] is to minimize $\frac{1}{2}\|w\|^2$ and the sum of errors ξ_i and ξ_i^* which deviates larger than ε. The role of $\frac{1}{2}\|w\|^2$ in the objective function is to achieve generalization and avoid the problem of over-fitting in the learned regression function $f(x)$. C is a constant, and the proper choice of C is essential for good generalization power. The parameter C and ε in C-SVR and the parameter σ of radial basis kernel is fine-tuned, to create a good regression model from C-SVR formulation. The fine-tuned values of C, ε and σ are 1, 0.01 and 10 respectively.

Table 1 Goodness of linear model between AR_n and PWP results

AR_n	R-Square	MSE
AR_1	0.011	131.62
AR_5	0.028	129.65
AR_{10}	0.055	126.30
AR_{20}	0.117	118.50
AR_{30}	0.196	108.38
AR_{40}	0.281	97.35
AR_{50}	0.364	86.45
AR_{60}	0.441	76.37
AR_{70}	0.507	67.53

AR_n	R-Square	MSE
AR_{90}	0.602	54.53
AR_{100}	0.642	49.05
AR_{110}	0.675	44.39
AR_{120}	0.700	40.94
AR_{130}	0.713	39.02
AR_{140}	0.713	39.14
AR_{150}	0.701	40.69
AR_{160}	0.678	43.87
AR_{170}	0.646	48.36

SVR Forecast models from the Historical data (SVR-Historic)

Two regression models are created from the SVR formulation discussed in the previous section, they are SVR-Historic and SVR-Adaptive. SVR-Historic model learns from the historic data, whereas the SVR-Adaptive model learns from both the historic data and the real-time streaming data. Both the models are discussed in the sub-sections below. Forecasting PWP 24 hours ahead is accomplished by training the SVR with future PWP values. The SVR model is trained for AR_{130} antecedent rainfall conditions from the current real-time and the PWP that developed 24 hours later. Therefore, to the learned model, if the current AR_{130} value is given, from the learned knowledge, the SVR model forecasts the PWP that is expected to develop 24 hours later.

SVR – Historic

The SVR model is trained using the data from July-2011 to December-2015. Radial basis function kernel is generated from the input training data and the weight vectors and bias terms are learned by minimizing the error variables ξ_i and ξ_i^*. The regression function thus learned is given as $f(x) = 358.34\phi(x) + 0.454$, with W as 358.34 and γ as 0.454, and $\phi(x)$ is the kernel function computed out of the training data. To assess the quality of the trained result, 10 fold cross validation is done on the training data, which resulted in a total Mean Squared Error of 41.7 and r-squared correlation coefficient as 0.718.The trained model is then used to forecast the period 2016-January to 2016-November. Forecast results are shown in Fig-5. Forecasted pore pressure values are compared with the actual pore pressure values, which arrives 24 hours later from the forecasted time. The results of the same are discussed in the section Results Discussion.

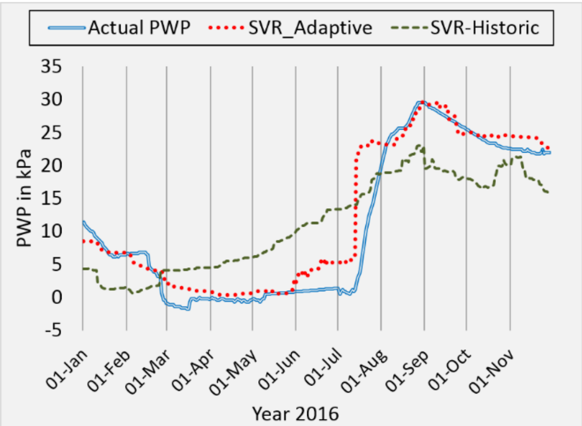

Fig.5Plot of actual *PWP* values and the forecasted *PWP*values

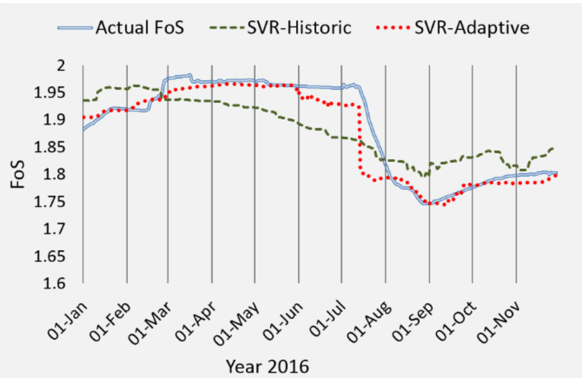

Fig.6 Plot of actual FoS values and the forecasted FoS values

SVR – Adaptive

Changes happening in the slope are not necessarily seasonal all the time, due to several factors like stabilization or unstabilization in certain regions of the slope, variation in ground water table, previous years wilting point, the amount of pre-monsoon and post-monsoon rainfall received etc. For instance, in Fig-3, two peaks for PWP are noticed for the years, 2012-2105. Whereas for the year 2011 and 2016, there is only one peak noticed. Therefore, a model created from the historical data alone will not be sufficient to cater to the changes happening in the slope. Hence we modified the SVR formulation to adapt itself in real-time along with the streaming real-time data to efficiently forecast the future behavior of the slope. By adapting means, along with the historical data, the SVR algorithm learns the real-time data and updates the kernel function $\phi(x)$, weight W and γ in real-time, thereby the learned model has the knowledge from the historical data, and the current state of the environment from the real-time data. This knowledge helps in improving the forecast accuracy. Using the historical data from July-2011 to December-2015, and real-time data from January-2016 onwards, the period of January-2016 to November-2016 is forecasted. The forecast results are shown in Fig-5 and the results are discussed 'Results Discussion' section.

Factor of Safety (FoS) and Amrita's Early Warning System (EWS)

The landslide mechanism in Munnar mainly depends on the rainfall duration, rainfall intensity, pore-water pressure distribution underneath the soil, ground water table and soil properties. After extensive study of different slope stability models, we chose Iverson's model (Iverson 2000), for computing the FoS. We have used PWP values instead of the simulated pressure values in Iverson's model to calculate the FoS of the slope. FoS of the slope forms one of the input for our Early warning System (EWS). Our EWS consists of three levels of warnings, Early, Intermediate and Imminent. 'Early level' of early-warning' is issued when the rainfall intensity crosses a threshold (Caine 1980). Since the early level warning is based on rainfall threshold, it's a regional level warning, and it is applicable for Munnar area wide. 'Intermediate' level warning is issued, when the Factor of Safety (FoS) value of the slope is less than 1. 'Immediate' level of early warnings are issued when significant displacements are noticed from movement sensor or when crack occurrences are observed in Geophones. Intermediate and Immediate level warning is a site specific warning and is applicable to the deployment site and the areas in the near vicinity of the deployment site. After the deployment of our system, the people wait for the Intermediate warning and then vacate themselves and their belongings. There is limited time for the people to vacate after the Intermediate level warnings. The forecasted PWP and FoS values gives 24 hours extra time for issuing the Intermediate level warning. Actual FoS values and the forecasted values are shown in Fig-6. Results are discussed in the next section.

Results Discussion

Forecasted PWP, FoS results from the SVR-Historic and SVR-Adaptive models are compared with the actual

PWP, FoS values. The results are shown in table-2 and table-3. We have used MSE and Pearson's correlation test as the metrics to compare the forecasted values with the actual values. From table-2, for PWP values, it can be seen that, the SVR-Adaptive model has a lesser MSE of 12.438 compared to the MSE of SVR-Historic, which is 48.726. From table-3, for FoS values, it can be seen that, the SVR-Adaptive model has a lesser MSE of 0.0007 compared to the MSE of SVR-Historic, which is 0.002.

Table-2 Comparison of forecasted PWPvalues from SVR-Historic and SVR-Adaptive with actual PWP values

Model compared with real-time PWP data	MSE	Correlation coefficient	p-value	95% Confidence Interval
SVR-Historic	48.726	0.804	2.2e-16	0.763,0.839
SVR-Adaptive	12.438	0.959	2.2e-16	0.950,0.969

Table-3 Comparison of FoS values computed from the forecasted $PWP$with actual FoS values

Model compared with real-time FoS data	MSE	Correlation coefficient	p-value	95% Confidence Interval
SVR-Historic	0.002	0.804	2.2e-16	0.763,0.839
SVR-Adaptive	0.0007	0.955	2.2e-16	0.950,0.969

Pearson's test for correlation coefficient is performed to compare the correlation between actual PWP, FoS values and forecasted PWP, FoS values from SVR-Historic and SVR-Adaptive models. From table-2, for PWP values, the correlation coefficient for SVR-Adaptive has a higher value of 0.959 with a relatively smaller confidence interval of 0.950 to 0.969 when compared to the SVR-Historic which has a correlation coefficient of 0.804 and a confidence interval of 0.763to0.839. Similarly from table-3, for FoS values, the correlation coefficient for SVR-Adaptive has a higher value of 0.955 with a relatively smaller confidence interval of 0.950 to 0.969 when compared to the SVR-Historic which has a correlation coefficient of 0.804 and a confidence interval of 0.763 to 0.839. For both PWP and FoS values, SVR-Adaptive model has a higher correlation coefficient and lesser MSE, from which we can interpret that SVR-Adaptive model performs better than the SVR-Historic model. The null hypothesis of the Pearson's correlation test states that, "True correlation does not exist between the actual PWP, FoS values and the forecasted PWP, FoS values". For the PWP and FoS forecast from both the models the p-value is found to be 2.2e-16 which is very low, therefore the null hypothesis of true correlation equal to zero is rejected in both the models. From Fig-5 it can be seen that the SVR-Historic model forecasts the two peaks that was observed in the historic data, whereas the SVR-adaptive model adapts to the changes in real time and the peak was linearized. Fig-5 and Fig-6 shows that, SVR-Historic model gives a generalized forecast and SVR-Adaptive model learns from the real-time data and adapts to the changes happening in real-time.

Conclusion and Future work

Rainfall distribution and cumulative rainfall for the years 2011-2016 are shown in Fig-1, along with the landslide warnings and landslide incidences in the deployment site and in other Munnar locations far from the deployment site. In this paper, we have shown from Fig-2 that the PWP data does not follow any standard distribution, so we chose a nonparametric method 'Support Vector Regression' to learn and forecast the PWP data 24 hours ahead of time. From fig-3, it can be clearly understood that the PWP build up is due to antecedent rainfall conditions. To understand the relation between AR_n and PWP, linear models are created and found that AR_{130} can better explain PWP variations and training data is created using the same. Two models SVR-Historic and SVR-Adaptive are presented in this paper. SVR-Historic learns and forecasts from the historical data alone. SVR-Adaptive learns from the historical data and the real-time data and forecasts the PWP in real-time. The kernel function $\phi(x)$, weight w and γ also changes in real-time, thereby adapting to the changes happening in real-time. SVR-Historic model is trained from July-2011 to December-2015 and tested for January-2016 to November-2016. SVR-Adaptive model is adaptively trained from July-2011 and tested for the period from January-2016 to November-2016. From the MSE values and correlation coefficient values of both the models for forecasting PWP and FoS, we can conclude that SVR-Adaptive model performs better than the SVR-Historic model. PWP and FoS forecast results from the SVR-Adaptive model correlates the actual PWP and FoS values approximately 95% of the times. So this model can be used to know PWP and FoS values with 95% accuracy 24 hours ahead, which will help the government and public with extra time for landslide preparedness. As a future work we would like to explore other nonparametric methods and compare them with SVR-Adaptive method and also perform probabilistic forecasts, and include weather forecast for improving the forecasting accuracy.

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T Hemalatha (✉)

Amrita Center for Wireless Networks and Applications, Amrita School of Engineering, Amrirapuri campus, Amrita Vishwa Vidyapeetham, Amrita University, Kollam 690525, India

E-mail: hemalathat@am.amrita.edu

Maneesha Vinidini Ramesh

Amrita Center for Wireless Networks and Applications, Amrita School of Engineering, Amrirapuri campus, Amrita Vishwa Vidyapeetham, Amrita University, Kollam 690525, India

E-mail: maneesha@amrita.edu

Venkat P Rangan

Office of the Vice Chancellor, Amrita Vishwa Vidyapeetham, Amrita University, Coimbatore, 690525, India

E-mail: venkat@amrita.edu

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