The interaction of seismic events with geo-environmental conditions and anthropogenic activities may exacerbate the risk of landslide hazard in a mountainous region. As an example of this, the 2005 Kashmir earthquake triggered many shallow to deep slope failures, which were further intensified in the following years by human activities notably along road networks, posing a long-term hazard. Hence, this study was planned to evaluate the effectiveness of landslide susceptibility prediction along an earthquake-affected road section of Neelum Highway using six different data-driven models. We applied analytical hierarchy process as a heuristic approach, weight of evidence and index of entropy as statistical models and multi-layer perceptron, support vector machine and binary logistic regression (BLR) as machine learning models. Initially, 224 landslide locations were marked through field surveys to prepare a landslide inventory, which was further randomly divided into training (70%) and testing (30%) datasets. Then, 13 landslide causative factors (LCFs) were extracted from geospatial database and analysed by measuring collinearity among factors and assessing their contribution to landslide occurrence using different feature selection methods for inclusion in susceptibility modelling. Thereafter, six employed models were trained to produce landslide susceptibility maps of the investigated road section. Finally, the area under receiver operating characteristics (AU-ROC) curve and various statistical measures were applied to validate and compare the performance of modelled landslide susceptibility. The results revealed that no collinearity issue exists among all 13 LCFs, and all six models exhibited satisfying performance in predicting landslide susceptibility of study area. However, BLR model has produced the most promising and optimum results as compared with other models with AU-ROC (0.881), Matthew's correlation coefficient (0.609), Kappa coefficient (0.604), accuracy (0.797) and F-score (0.787). The outcomes of this study can be used as pertinent guide for preventing and managing the landslide disaster risk along Neelum Highway and beyond.

**KEYWORDS**
heuristic model, Kashmir Himalaya, landslide susceptibility, machine learning algorithm, statistical model
1 | INTRODUCTION

A landslide is a kind of complex geohazard in the mountainous terrains around the world that imposes an enormous threat to population, sources of livelihood and infrastructure. It occurs as a result of the interplay of geological events, geo-environmental factors and anthropogenic activities (Aleotti & Chowdhury, 1999; Guzzetti, 2005). On Earth, the Himalaya is one of the most susceptible mountainous terrains for destructive landslide hazards where combined impact of periodic seismicity, monsoon rains and human activities along unstable slopes often aggravate the phenomena of landsliding (Garrard, 1994; Rusk et al., 2022). The region of Kashmir Himalaya, falling in seismically active zone of western Himalayan belt, faced devastating seismic events in the past with the most recent catastrophic earthquake of 2005 (Gardezi et al., 2021; Sana & Nath, 2017). This earthquake event and aftershocks had triggered more than 2000 landslides over an affected area of around 7500 km² (Owen et al., 2008). The devastation badly affected the major components of Neelum Highway and resulted in severe damaging and blocking of main route even 3 months after the main event (Basharat, Rohn, Baig, & Khan, 2014; Rahman et al., 2014). This mega-event and post-earthquake shaking highly deformed the rocks and significantly increased the vulnerability of slopes for landsliding that led to the development and reactivation of landslides upon subsequent interaction with other extrinsic variables (Khattak et al., 2010). Therefore, it is crucial to assess the possible zones of slope failures in this region using modern practices to formulate effective landslide mitigation strategies. For this purpose, the landslide susceptibility mapping is considered as a primary component in landslide hazards and risk assessment in past decades (Huang et al., 2020).

Landslide susceptibility represents the spatial probability of landslides in a particular region based on local geo-environmental conditions and causative factors. Over the years, a number of studies were performed by several investigators, for example (Achour & Pourghasemi, 2020; Aditian et al., 2018; W. Chen et al., 2019; Guzzetti, 2005; Hong et al., 2020; Huang et al., 2020; Merghadi et al., 2020; Saha & Saha, 2020; Q. Wang et al., 2016; H. Wang et al., 2021; T. Zhang et al., 2018) to assess the landslide susceptibility using different modelling approaches, which can be generally categorized into physical-based and data-driven models. In general, the physical-based models compute the quantitative stability factor of slope to simulate landslide failure in certain areas by taking geo-technical properties of landslides into account that control the processes of landslide occurrences. Moreover, these models are also applied in various studies to analyse probabilistic landslide hazard over a large scale in heterogeneous conditions, while in some cases they have been adopted for susceptibility and hazard assessment based on different landslide movement types (Ciurleo et al., 2017; Medina et al., 2021). However, regional-scale application of these models for landslide susceptibility assessment is still a challenge due to high operational cost for extensive site-specific data acquisition and uncertainties associated with determination of soil properties (Tofani et al., 2017). In contrast, data-driven models ignore complex physical processes involved in landslide occurrences and require limited computational cost to exhibit more reliable results with high accuracy in predicting regional landslide susceptibility. They can be categorized into heuristic, statistical and machine learning models (Huang et al., 2020). The heuristic approach can execute landslide susceptibility prediction (LSP) by measuring the weight values for each conditioning factor based on expert opinion derived from the field knowledge using rating techniques, mainly including analytical hierarchy process (AHP) and weighted linear combination (WLC) (Shahabi & Hashim, 2015). On the other hand, statistical approach predicts the probability of landsliding through numerical relationship between observed landslides and causative factors (Erer & Düzgün, 2012) using either multivariate or bivariate modelling techniques. The multivariate statistical models quantify the combined relationship between the dependent variable and several independent variables for landslide probability analysis irrespective of factor class contribution of each conditioning factor. The prominent multivariate methods, widely explored for quantitative susceptibility assessment of landslide, include principal component analysis (Faraji Sabokbar et al., 2014), discriminant analysis (Zêzere et al., 2017), linear multivariate regression model (Arabameri et al., 2019), and adaptive regression splines (Y. Wang & Rathje, 2015). Whereas, the bivariate statistical models evaluate the independent relationship of each landslide governing predictors with spatial distribution of past landslide events. The bivariate techniques such as certainty factor (Hong et al., 2017), evidential belief function (Ding et al., 2017), frequency ratio (Li et al., 2017; Yalcin et al., 2011), generalized linear models (Goetz et al., 2011; Huang et al., 2020), information value method (W. Chen et al., 2014; Du et al., 2017), index of entropy (IoE), and weight of evidence (WoE) (Liu & Duan, 2018; Regmi et al., 2014) have been successfully applied in various studies to produce landslide susceptibility maps (LSM) with significant model accuracy. Machine learning (ML) models, a powerful group of data-driven approaches, use computational algorithms to analyse the nonlinear relationship between events and factors. These techniques are rapidly evolving in the research domain of landslide susceptibility modelling, due to high precision rate and adequate handling of complex data with high predictive accuracies, as compared with conventional statistical approaches. The commonly used ML methods in LSP include AdaBoost (Hong et al., 2018), binary logistic regression (Huang et al., 2020; Pradhan & Jebrul, 2017), decision tree (Dou et al., 2019), gradient boosting (T. Chen et al., 2020; Sahin, 2020), K-nearest neighbours (Pradhan & Jebrul, 2017), kernal logistic regression (Aditian et al., 2018; Park et al., 2013), multilayer perceptron (MLP) (Bui et al., 2020; Zare et al., 2013), naïve bayes (W. Chen et al., 2017; Tien Bui et al., 2012), neuro fuzzy (Pradhan, 2013), random forest (T. Chen et al., 2020; Dou et al., 2019) and support vector machine (SVM) (Bui et al., 2020; Pradhan, 2013).

Although, several approaches have been proposed for producing LSMSs in the existing literature, still no consensus has developed among scholars around the globe as to which model is more reliable and best suited for predicting landslide susceptible areas in different terrains. However, researchers recommend that these models should be applied and tested in different geo-environmental conditions,
where landslide activities are governed by multiple processes to validate the quality and accuracy of the model used (Pourghasemi & Rahmati, 2018). Moreover, a few studies suggest the practical application of different models and their comparative analysis in a similar area should be investigated to obtain a robust model for LSP. Therefore, in light of the foregoing consideration, it is important to implement and compare popular data-driven techniques in a given area for better understanding of LSP.

As the most disastrous and tectonically active region of Kashmir Himalaya, Muzaffarabad–Neelum trunk road was chosen as example for the present study. This road section experienced a devastating 7.6 $M_s$ earthquake in 2005 that triggered enormous landslides along natural and cut slopes with subsequent blockage of accessed roads (Kamp et al., 2008; Owen et al., 2008). The main seismic event and its aftershocks caused extensive fissures, cracks, lateral and back scarps in surrounding slopes of this road section, which resulted in frequent and progressive slope failure specially in extreme weather conditions. Hence, it is essential to understand and recognize the persistent patterns of landslide hazard for mitigating future slope failures in this region. Most studies have been conducted to identify the occurrence, size, spatial distribution and pattern of landslides associated with the 2005 Kashmir earthquake, for example, (Ahmed et al., 2021; Basharat et al., 2016; Basharat, Rohn, Baig, & Khan, 2014; Basharat, Rohn, Baig, Khan, & Schleier, 2014; Jadoon et al., 2015; Kamp et al., 2008; Khan et al., 2013; Khattak et al., 2010; Owen et al., 2008; Saba et al., 2010; Shafique, 2020; Shafique et al., 2016). However, only a few studies were focused on landslide susceptibility mapping using conventional quantitative techniques such as Basharat et al. (2016) and Kamp et al. (2008), where those work undertook LSP for earthquake-affected areas based on semi-quantitative approach (AHP). Recently, Ahmed et al. (2021) demarcated the landslide prone areas along a small portion of Neelum road using WoE method and investigated the geo-technical aspect of specific landslides. Though these studies demonstrate landslide hazard maps which were modulated by limited number of landslide conditioning factors, a comprehensive study on spatial prediction of landslide susceptibility to draw a robust conclusion about prediction ability of different data-driven techniques is still lacking for this region. We, therefore, undertook an extensive analysis of machine learning techniques (MLP; SVM; BLR) and their comparison with heuristic (AHP) and traditional statistical methods (IoE; WoE) to evaluate a robust model for accurate LSP and to identify the relationship between the geo-environmental factors and landslide distribution along an earthquake-affected road section in Kashmir Himalaya.

2 | STUDY AREA

The study area lies in the western part of main landmass of the State of Jammu and Kashmir and is approximately situated between the longitudes 73°26' E to 73°56' E and latitudes 34°21' N to 34°40' N. It is positioned along the main drainage of the Neelum River and covers an area of ~287.97 km² (Figure 1c,d). Athmuqam city is located in the eastern part, Nauseri in the central part, while Muzaffarabad city falls in the western part of the study area connected by a major trunk road. This road is the lifeline for more than 0.3 million inhabitants of Neelum valley. Moreover, it has a significant strategic importance as it is located along Pakistan–India Line of Control. Topographically, the study area is dominantly characterized by hilly terrain with elevation ranging from 632 to 2857 m above sea level (a.s.l). The terrain in the northern and central regions of the study area are relatively higher, with altitude exceeding ~1100 m a.s.l, as compared with the western region, which has mean elevation of ~800 m a.s.l (Figure 1d). The settlements in the study area are widely dispersed along gentle slopes, river terraces and valley floors, which increases the pressure on the land and environment due to high population density and small land holdings. The climate of the region is humid, humid tropical and sub-tropical highland with an average annual rainfall of 1400 mm. Mean maximum and minimum temperatures in the area during summer are about 20–34°C and in winter 2–18°C, respectively (Bashir & Hanif, 2018).

2.1 | Geomorphological setting

The study area being a western part of Lesser and Sub-Himalayas is classified into three geomorphological zones, that is, mountainous terrain, the lower hills of valley slopes and foot slopes of fluvial sediments along the major tributaries. The valley floor in the northern part is deeply incised by the Neelum River and its feeding tributaries, having a relief of about 2200 m. The rapid flow of the river in this region with an average discharge of nearly 230 m³/s has resulted in fluvial incision forming a steeper low valley with slopes exceeding 50°. This landscape reflects a high-relief energy resulting in a V-shaped valley with high erosion rate. The back slopes above these valley slopes are less steep with average slopes of about 15–30° (Kamp et al., 2008). Talus or slided mass, fluvial deposits, terraces, alluvial fans and glaciofluvial deposits are major geomorphic accumulations observed in the study area.

2.2 | Geological and tectonic settings

Geologically, the area is comprised of sedimentary, metamorphic and igneous rocks, which ranges from Precambrian to Miocene (A. Hussain & Khan, 1996). The lithostratigraphic units exposed in the northern part of the study area are Precambrian Salkhala Formation comprising t alc- quartzitic schists, graphitic schist with subordinate marble and Cambrian Jura Granite of gneissic and porphyritic type with doleritic intrusions at certain places. The Panjal Formation consist of greenstone, andesitic flows with bedded tuff and meta-carbonates with agglomeratic slate, phyllite and mica schist is exposed in the central part (Fontan & Schoppe, 1994). The Tertiary fluvioclastic deposits of Murre Formation containing sandstone, mudstone and siltstones formed as a consequence of Himalayan Orogeny occupy the central and southern parts of the study area. The Palaeocene–Eocene carbonate deposits unconformably overlie along the cherty dolomitic limestone of Cambrian Abbottabad Formation near Muzaffarabad. The Quaternary deposits of fluvial origin are
FIGURE 1  Location map of study area (a) geographical position of Himalaya; (b) geological map of Himalaya (Searle & Treloar, 2019); (c) extent map indicating structural set-up of NW and Kashmir Himalaya (Baig, 2006); (d) route map of Neelum Highway.
mostly exposed along the lower slopes and terraces (A. Hussain & Khan, 1996; Shah, 2009).

The study area lies in the core and limbs of a prominent structure, that is, Hazara–Kashmir Syntaxis (HKS), which implicates the region as complex tectonic zone (Calkins et al., 1975; G. Hussain et al., 2020). Tectonically, the area is sub-divided into three units: (a) the youngest Tertiary Molasse deposit in the core of HKS surrounded by the Main Boundary Thrust (MBT) and Pre-molasse sequences, (b) the tholeiitic–alkaline volcanic and agglomeratic slates, extending as a linear belt between the MBT and the Panjal Thrust, (c) the oldest Precambrian meta-sediments and Cambrian granites exposed on the eastern and western limbs of HKS (Bossart et al., 1988). The MBT in the study area constitutes a suture along which remnants of a Palaeozoic ocean floor sediment, the Panjal Volcanics and the agglomeratic slates have been thrust over the Murree Formation (Treloar et al., 1992) (Figure 1b,c). The western limb of the HKS is more complicated by the emergence of Balakot–Bagh Fault (BBF), which emplaced the Cambrian dolomite of Muzaffarabad Formation over Miocene Murree Formation (A. Hussain et al., 2009). Along BBF, seismic activity of the 2005 earthquake had generated a mean vertical displacement of ~4.3 m in the central segment of the fault near Chela Bandi, Muzaffarabad (Kaneda et al., 2008). This event created many cracks on the hill slope resulted in slope failure of bed rock as well as colluvial deposits along major roads, natural slopes and other man-made slope cuts (Owen et al., 2008).

3 | DATASET PREPARATION

The landslide susceptibility modelling in a given area involves the collection of data on landslide occurrence, geospatial database construction on landslide conditioning factors and probability modelling for landslide susceptible areas based on the relationship between landslide events and their triggering factors followed by validation of produced models (Guzzetti, 2005; Regmi et al., 2014). For this purpose, the dataset we used to construct different thematic layers includes ALOS PALSAR DEM with 12.5 m resolution, geological maps of Geological Survey of Pakistan (GSP), published reports and research articles, Landsat-8 Images downloaded from the US Geological Survey (USGS) website, Google Earth imageries, rainfall data (Tropical Rainfall Measuring Mission and Pakistan Meteorological Department) and detailed field mapping (Table 1).

### 3.1 | Landslide inventory mapping

The preparation of accurate landslide inventory is an important step for investigating the possible landslide hazards and susceptibility mapping (Guzzetti et al., 2012; Hao et al., 2020). These inventory maps demonstrate information about the landslide locations, its dimensions and types of mass movements that have triggered in the past. In the present study, landslide distribution has been extracted from previous literature (Basharat, Rohn, Baig, & Khan, 2014; Kamp et al., 2008; Owen et al., 2008), historical records of GSP and visual interpretation of Google Earth images (2003–2020). The extensive field survey was also carried out during March–April 2021 for validation, precise demarcation of landslides area and their characteristics. For this purpose, landslide dataset, which was recorded systematically during field observation using GPS-based Field MOVE Clino (Android App) was finally converted into vector database in GIS for preparation of landslide inventory map. A total of 224 landslide events were recorded during this study and are illustrated in Figure 2.
The landslide distribution analysed during fieldwork reveals that geo-environmental and anthropogenic factors are controlling mass movements in most part of the study area, whereas co-seismic landslides are mostly concentrated along the proximity of BBF, particularly around the north-western portion of hanging-wall slopes of fault trace. Furthermore, the types of movement are translational, rotational and complex (Figure 3). The clustered failures were mostly shallow involving bedrock to superficial accumulations, whereas the size of the materials ranges from a few m³ to thousands of m³. Based on landslides inventory mapping, the study area can broadly be categorized into three sections: (a) north-eastern section is a narrow dissected valley where triggered landslides are linked with steeply jointed rocks of Precambrian metamorphic and Cambrian granites; (b) comparatively broader valley in the central section having less steep slopes (<50°) comprising of landslides with variegated lithologies of Tertiary molasses and Quaternary fluvial terraces; (c) in the western section, landslides are developed in Cambrian dolomitic limestone and Palaeocene–Eocene marine sediments mostly clustered along the proximity of active BBF.

In the current study, the compiled landslide inventory was converted as landslide point data based on sampling strategy specified by Dou et al. (2020) representing multiple points from landslide body, whereas equal number of non-landslides points were randomly selected from stable areas. This dataset was then converted into training (70%) and testing (30%) data using ArcGIS 'Subset' tool for modeling landslide susceptibility and its validation.

3.2 | Landslide causative factors

The selection of landslide causative factors (LCFs) generally relies on the available data, scale and nature of the study area as there are no set criteria or universal agreement until now (Merghadi et al., 2020; Oommen et al., 2018). Our study area lies in the Himalayan region
where active tectonics, geo-environmental variables and anthropogenic activities are main contributors of mass movements. Therefore, 13 parameters consisting of geological factors (lithology and proximity to fault), geomorphic factors (slope, aspect, curvature, relative relief, topographic wetness index [TWI], proximity to drainage and lineaments), environmental factors (Normalized Difference Vegetation Index [NDVI], land use and precipitation) and anthropogenic factor (proximity to roads) were selected as LCFs and were standardized to a common cell size (12.5 × 12.5 m). Furthermore, we classified categorical LCFs according to heuristic classification scheme of related thematic

**FIGURE 3** Field photographs (a) landslide in Murre Formation near Deolian village; (b) several episodes of slope failure in Salkhala Formation near Bari area; (c) Dhani landslide triggered in the hanging wall of Balakot–Bagh Fault; (d) multiple phases of Panjgrain landslide caused by combined interaction of road- and river-cutting and fragile lithology; (e) Shahkot landslide initiated due to the water seepage from irrigation channel on upper half and toe-cutting.

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| Landslide conditioning factors | Sub-classes                                                                 | Role of causative factors on slope failure                                                                                                                                         | Classification method/references                                                                 |
|-------------------------------|----------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|
| Lithology                     | Alluvium, Murree Formation, Patala Formation, Lockhart Limestone, Hangu Formation, Panjal Metasediments, Panjal Volcanics, Jura Granite, Muzaffarabad Formation, Hazara Formation, Salkhala Formation | Degree of landslide vulnerability is directly influenced by geological characteristics of an area. The probability of landslides typically increases along slopes with low shear strength (Bahrami et al., 2020) | Classified as per data source (A. Hussain & Khan, 1996; Shah, 2009)                             |
| Proximity to faults (m)       | 0–250; 250–500; 500–750; 750–1000; >1000 | Generally, an area closer to the fault lines is more susceptible to slope failures than the area further away (Sun et al., 2020)                                                                                       | Equal interval, adopted from (Basharat, Rohn, Baig, & Khan, 2014; Ikram et al., 2021)               |
| Slope angle (°)               | <10; 10–20; 20–30; 30–40; 40–50; 50–60; > 60 | The phenomena of landsliding usually occurs in the landforms with higher slope angles (Saha & Saha, 2020)                                                                                                               | Classification interval were determined by considering the intensities of landslides in the study area. Equal interval (W. Chen et al., 2019) |
| Aspect                        | Flat; North; Northeast; East; Southeast; South; Southwest; West; Northwest | The slope direction, to a degree, dictates the frequency of landslides (Regmi et al., 2014)                                                                                       | Remained unmodified (Merghadi et al., 2020)                                                        |
| Curvature                     | Concave; Flat; Convex                                                     | Probability of landslide increases with decrease in curvature values (Bera, Guru, & Ramesh, 2019)                                                                                   | Positive values (>+0.1) indicate convex, negative values (<-0.1) represent concave and (-0.1 to +0.1) shows flat curvature (Hu et al., 2021) |
| Relative relief (m)           | <1000; 1000–1500; 1500–2000; 2000–2500; >2500 | High relative relief within a unit area indicates high slope and therefore, susceptible for landslide (Basu & Pal, 2019)                                                                                      | Equal Interval, (Basharat, Rohn, Baig, & Khan, 2014; Qiu et al., 2018)                              |
| Topographic wetness index (TWI) | <5; 5 to 9; >9                                                   | Higher TWI values can relate to higher chances of slope failure (Goetz et al., 2011; Y. Wang, Fang, et al., 2020)                                                                  | Geometric Interval (Ikram et al., 2021)                                                             |
| Proximity to drainage (m)     | 0–100; 100–200; 200–300; >300                                           | Areas near to drainage are more vulnerable to landslide occurrence due to high rate of soil erosion (Du et al., 2017)                                                               | Influence of drainage transport water in culminating landslides as observed in fieldwork, Equal interval (Ikram et al., 2021) |
| Lineament density (km/km²)    | 0–0.45; 0.45–0.9; 0.9–1.35; 1.35–1.9; 1.9–3.5 | Positive relationship exists between landslide occurrence and lineament density (Bera et al., 2019)                                                                                   | Equal interval (Saha & Saha, 2020)                                                                       |
| Normalized Difference Vegetation Index (NDVI) | >15%; 15%–30%; >30% | Landslide probability increases in the areas with low NDVI values (Dou et al., 2015; Huang et al., 2020)                                                                              | Classified on the basis of percentage of vegetation cover, Equal interval (Dou et al., 2015)             |
| Landuse                       | Barren; forest; grassland; settlements; water                             | Landuse have variable influence on landslide probability, while settlements and barren lands have positive relationship with slope failure (W. Chen et al., 2019)                                     | Classified according to scheme adopted by Landuse Planning Department of AJK Government http://lupajk.gov.pk/ |
| Precipitation (mm)            | <1000; 1000–1200; 1200–1400; >1400                                      | High precipitation rate detaches the slope material and increases the landslide possibility (G. Zhang et al., 2016)                                                               | Equal interval (Tien Bui et al., 2016)                                                                |
| Proximity to roads (m)        | 0–100; 100–200; 200–300; >300                                           | Areas near to road cuts are more vulnerable to landslides (W. Chen et al., 2021)                                                                                                | Based on observation of road clear-cutting and construction activities, Equal interval (Ahmed et al., 2021; Rahman et al., 2014) |
Figure 4
Landslide causative factors utilized for landslide susceptibility prediction of study area.
information, whereas continuous variables were classified based on spatial distribution of landslides and trends in the literature using equal and geometric interval methods in ARC GIS (W. Chen et al., 2018; Huang et al., 2021). The classification standards of selected LCFs and their role in culminating landslide are briefly described in Table 2.

3.2.1 | Geological factors

The fragile lithology, sheared and jointed rocks affects the stability of material, which often leads to landslide event along steep slopes (Basharat, Rohn, Baig, & Khan, 2014; Kamp et al., 2008). Therefore, in the present study, lithology and distance to fault were taken as input variables for landslide susceptibility modelling.

Lithology

Lithology is classified in terms of rock and soil composition, whereas its mechanical properties and composition controls the permeability and strength of slope forming materials, thus considered as an important parameter in landslide susceptibility mapping (Ayalew & Yamagishi, 2005; Yalcin et al., 2011). The information on the spatial distribution of lithological formations were identified from the geological maps of GSP (A. Hussain et al., 2006, 2009; A. Hussain & Khan, 1996). Eleven geological formations are exposed, which
comprised of lithological units derived from igneous, metamorphic and sedimentary origin such as granite, doleritic intrusions, schist, slates, phyllites, marble, basaltic volcanic flows, dolomitic limestone, cherty nodular limestones, marine shales, sandstone, siltstone and mudstone with Quaternary fluvial terrace, alluvial fans and colluvial deposits at certain places (Figure 4h).

Proximity to faults
The faults are categorized as zone of weakness and are responsible for rocks fracturing and jointing, which controls the failure mechanism in the form of rock sliding and wedge sliding. In the proximity to faults, increasing fracture density enhances the permeability of terrain and reduces the slope strength, therefore it is considered as the important influencing parameter for slope failures in modelling landslide susceptibility (Dou et al., 2020; Pradhan & Jebur, 2017). The study area being part of northeastern Himalayas of Pakistan is recognized as the zone of high seismicity with active thrust faulting often contributing seismic hazard accompanied by lethal landsliding (Gardezi et al., 2021). The most recent seismic event of 2005 had produced thousands of landslides with extensive cracks, fissures and bulging slopes in the region (Basharat, Rohn, Baig, & Khan, 2014; Kamp et al., 2008; Owen et al., 2008). The field observations recorded in the study area revealed that rocks fracturing was common over a proximity of 500 m from fault, whereas the intense zones of fractures were seen in the range of 0–150 m. Therefore, for understanding the relationship between fault presence and landslide occurrence, five buffer zones were created along the major fault lines in ArcGIS ‘Euclidian distance’ tool and classified accordingly: <150 m, 150–300 m, 300–450 and >500 m (Figure 4i).

3.2.2 | Geomorphic factors

Geomorphic parameters are considered as major influencing terrain factor in landslide occurrence (Pourghasemi & Rahmati, 2018). The geomorphic parameters we used in this study are briefly described below:

Slope angle
Slope angle plays a vital role in contributing landslide activity and is considered an important causative factor in susceptibility modelling of landslide hazards (Hu et al., 2020; K. Wang, Xu, et al., 2020). The common slope failure generally depends on the degree of cohesion in slope material and inclined angle where gravity exerts a sliding force on slope mass (Pourghasemi et al., 2018). In our case, the slope gradient ranges from 0 to 80° and were reclassified into seven classes based on landslide distribution analysed during field study. The slope angle categorized with 10° interval as: <10°, 10–20°, 20–30°, 30–40°, 40–50°, 50–60° and >60° (Figure 4a).

| Year | Muzaffarabad | Muzaffarabad airport | Barakot | Balakot | Deolan | Nauseri | Atthmuqam | Chakothi |
|------|--------------|----------------------|---------|---------|--------|---------|-----------|---------|
| 2001 | 1270.1       | 1328.3               | 1317.1  | 1169.9  | 1198.3 | 1084.1  | 744.7     | 1077.3  |
| 2002 | 1323.4       | 1478.7               | 1036.9  | 1335.2  | 1376.5 | 1301.1  | 532.6     | 903.3   |
| 2003 | 1315.8       | 1455.9               | 1020.1  | 1802.9  | 1328.9 | 1549.3  | 961.5     | 1095.7  |
| 2004 | 1487         | 1688.4               | 1485.1  | 1466.4  | 1436.2 | 1562.1  | 858.9     | 998.23  |
| 2005 | 1380.6       | 1582.6               | 1128.8  | 1456.5  | 1376.4 | 1562.8  | 661.2     | 1045.7  |
| 2006 | 1951.6       | 2150.3               | 1692.3  | 2316    | 1755.6 | 1651    | 1232.9    | 1386.7  |
| 2007 | 1279.9       | 1466.2               | 1520.6  | 1427.4  | 1309.3 | 1146.8  | 832.7     | 1012.8  |
| 2008 | 1710.2       | 1870.6               | 1593.8  | 1711.9  | 1645.9 | 1260.4  | 825.2     | 1139.8  |
| 2009 | 1352.7       | 1444.8               | 1270.6  | 1311.3  | 1395.2 | 1175.6  | 541.2     | 946.5   |
| 2010 | 1536         | 1738.1               | 1668    | 1780.5  | 1496.1 | 1491    | 790.3     | 1298.3  |
| 2011 | 1577.7       | 1896                 | 1407.4  | 1326.1  | 1385.3 | 1344    | 746.3     | 1086.2  |
| 2012 | 1461.4       | 1524.2               | 1515    | 1382.4  | 1368.2 | 1047.8  | 717.4     | 1191.2  |
| 2013 | 1363.6       | 1392.3               | 1537.8  | 1425.9  | 1426.1 | 1232    | 924.4     | 1053.9  |
| 2014 | 1453.4       | 1488.6               | 1561    | 1586.4  | 1492.8 | 1159    | 939.3     | 1241.6  |
| 2015 | 1741.7       | 1802                 | 2396.9  | 1595.5  | 1675.3 | 1788.9  | 1041.5    | 1202.8  |
| 2016 | 1229.2       | 1475.5               | 1274.5  | 1269.5  | 1123.3 | 1040.8  | 654.9     | 1033.8  |
| 2017 | 1446.27      | 1542.7               | 1335.8  | 1223.4  | 1369.2 | 1101.2  | 993.7     | 1127.8  |
| 2018 | 1327.4       | 1390.2               | 1421.7  | 1477.6  | 1356.4 | 1288.6  | 704.14    | 999.5   |
| 2019 | 1591.3       | 1681.5               | 1588.3  | 1680.5  | 1488   | 1465.2  | 1025.5    | 1239.8  |
| 2020 | 1496         | 1625.8               | 1539.9  | 1475.3  | 1401.8 | 1314    | 988.2     | 1055.8  |
| Mean | 1463.8       | 1604.3               | 1465.5  | 1511.3  | 1420.2 | 1328.3  | 835.8     | 1106.8  |
FIGURE 5  Flow chart of applied methodology
Aspect
The aspect of slope is generally described as slope facing direction having significant impact on several processes (vegetation distribution, discontinuities patterns, weathering and moisture retention), which can directly or indirectly affects the landslide phenomena (Shahabi & Hashim, 2015). The environmental conditions such as snow melt precipitation pattern and sunlight exposure also influence the slope stability with subsequent changes along particular slope direction (Ayalew & Yamagishi, 2005). The slope aspect in this study was classified as N, NE, E, SE, S, SW, W, NW and flat (Figure 4b).

Curvature
Slope curvature is one of the important geomorphological factors widely used as LCFs in landslide susceptibility mapping (Dou et al., 2015). It represents the concavity, flatness and convexity of terrain surfaces that stimulates the flow velocity and divergence of runoff water and controls the occurrences of landslide (Bera et al., 2019). The curvature values for current study were reclassified as flat (zero curvature), concave (-tive curvature) and convex (-tive curvature) (Figure 4c).

Relative relief
The relative relief represents the altitude difference between highest and lowest points in a unit area. It has a significant relationship with mass movement and is considered as primary risk factor that controls the frequency of landslides. Various landslide studies have shown that slope failures are scarce at higher altitude (Pourghasemi et al., 2018). In the current study, the relative relief data obtained from DEM was sub-divided into five consecutive classes with an average interval of 500 m (Figure 4d).

Twi
Twi indicates the topographic control on local hydrological conditions, evaluated through soil saturated zones of an area with respect to catchment locations (K. Wang, Xu, et al., 2020). The degree of water distribution in a soil increases the pore pressure, which affect the soil, rock and vegetation condition on upslope resulting in slope failure (Sun et al., 2020). According to Beven and Kirkby (1979), it is defined as follows:

\[
TWI = \ln \left( \frac{a}{\tan \beta} \right),
\]

where \(a\) is expressed as the flow accumulation in certain point and \(\beta\) is measured as the local degree slope (radian). In the present study, the TWI values were calculated through DEM using ArcGIS operations and were reclassified as: <5, 5–9 and >9 (Figure 4i).

Proximity to drainage
The proximity to drainage is considered as an important landslide causative factor, influencing the slope stability in terms of erosion along the toes of slopes and by increasing the water saturation level in lower part of the slope (Bera et al., 2019). This effect become adverse when water-laden drainage drains the steep slopes and sliding zones because the fluvial incision and lateral cutting gradually favours the condition for mass movement (Sun et al., 2020). In the study area, the proximity to drainage was calculated through ‘Euclidean distance’ tool in GIS and was classified into four classes with an interval of 100 m: 0–100 m, 100–200 m, 200–300 m and >300 (Figure 4k).

Lineaments density
The lineaments pattern in a specific area can be expressed as linear topographic signatures controlled by geomorphic and tectonic processes. These features may affect the stability of slopes and increases the probability of slope failures (Ayalew & Yamagishi, 2005). The lineament patterns were extracted from Landsat 8 OLI imagery (pan-sharpened) by automated lineament extraction technique using LINE module in PCI Geomatica software, which were further validated with the help of interactive visual interpretation using DEM and geological maps of study area. The extracted lineaments were processed in ArcGIS by Euclidean density function to generate the lineaments density map with five classes: 0–0.45 km/km², 0.45–0.9 km/km², 0.9–1.35 km/km², 1.35–1.9 km/km² and 1.9–3.5 km/km² (Figure 4g).

3.2.3 | Environmental factors

NDVI
NDVI is measured as the degree of vegetation distributed in a region and is closely associated with water flow and penetration and soil erosion, which influence the landslide activity along slope surfaces (Huang et al., 2020). Therefore, it has been effectively utilized as a crucial parameter in landslide prediction modelling. In the current study, the values of NDVI were computed using Landsat 8 OLI multi-spectral imagery of 15 September, 2019 (https://earthexplorer.usgs.gov) using the following formula:

\[
NDVI = \frac{NIR - R}{NIR + R},
\]

where \(R\) is computed as the red spectral band and \(NIR\) is near infrared band of electromagnetic spectrum (Tucker, 1979). These values range from −0.15 to 0.56 and were categorized as <0.1, 0.1–0.3 and >0.3 (Figure 4e).

Land use
Land use is frequently used contributing factor in susceptibility modelling for landslide, especially in the mountainous terrain where natural process affect the slope stability of a region (Pourghasemi et al., 2018). The changes in land cover due to landscape modification for infrastructure, deforestation and farmland on steep slope directly influence the hydrological conditions, which affect the slope failure mechanism (Y. Wang, Fang, et al., 2020). The land use map of the study area was prepared by analysing Landsat 8 OLI images through supervised image classification technique in ArcGIS environment by correlating the land use map provided by Landuse Planning...
Department of AJK Government. The output of landuse types were categorized into five classes, that is, barren land, forest, grass land, settlements and water body (Figure 4f).

**Precipitation**

Various studies suggest that extreme events of precipitation affect the slope stability by triggering new landslides or reactivation of old landslide. Thus, the relationship of landslide occurrence with precipitation had been adopted as a critical LCF in predicting the landslide hazard around the globe (Huang et al., 2020). The effect of climate variations in study area during intense precipitation of monsoon season and winter westeries increases the infiltration and erosion rate along vulnerable slopes which influence the probability of rapid slope failure (Rahman et al., 2014). In this study, mean annual precipitation data of study area (2001–2020) were interpolated through inverse distance weighted (IDW) function in ArcGIS to generate the precipitation map (Table 3). This map was further classified into four classes: <1000 mm, 1000–1200 mm, 1200–1400 mm and >1400 mm (Figure 4m).

**3.2.4 | Anthropogenic factors**

The anthropogenic activities such as construction of buildings, roads, water channels and dams, terracing, stone quarries, excessive mining and deforestation, disturb the equilibrium state of slope material and increase the vulnerability of landslide hazard along steep slopes (Regmi et al., 2014). In this research, the proximity to roads was selected as the main anthropogenic factor influencing slope failures in the study area.

**Proximity to roads**

Roadcut being a site of anthropogenically disturbed slopes, can act as a catalyst for landslide occurrence in a mountainous region (Ayalew & Yamagishi, 2005). The excavation and uncontrolled blasting techniques for construction of roads alter the natural stability of slope and accelerate the probability of landslide incidences (Das et al., 2010). In the present study, the landslide failure zones due to slope cutting were observed at a distance of approximately 100–200 m to major road network. Therefore, we have generated proximity to road map comprising of four buffer zones: 0–100 m, 100–200 m, 200–300 m and >300 m (Figure 4j).

**4 | METHODOLOGY**

The methodological approach adopted for comparative assessment of different landslide prediction models is illustrated in Figure 5 and categorically explained below.

**4.1 | Landslide predictors analysis**

In this work, factor analysis of LCFs were adopted to identify the relevant predictors by measuring co-variation among multiple variables and assessing the relative importance of causative factors in landslide occurrence.

**4.1.1 | Collinearity analysis**

In landslide studies, collinearity among predictors may occur due to the linear association of two or more independent variables that reduces the predictive performance of susceptibility models. Therefore, it is important to diagnose and eliminate the collinearity problem between input variables before data mining (Merghadi et al., 2020). To address this issue, variance inflation factor (VIF) and Pearson’s correlation were performed as statistical tests in this research.

VIF helps to quantify multicollinearity that arise due to the linear relationship between one variable and another variable in a model (Di Napoli et al., 2020). Mathematically, it is computed as follows:

\[
VIF = \left(1 - R_i^2\right)^{-1}.
\]  

Here, \(R_i^2\) is the coefficient of determination calculated by regression analysis of ith predictors to other predictors (O’Brien, 2007). If VIF = 1, it indicates no correlation between one LCF to the remaining ones, whereas VIF > 5 or 10 reflects higher multicollinearity (Hong et al., 2020).

On the other hand, Pearson’s correlation is a statistical test that computes the extent of linear relationship between two predictors and their association with each other (Dou et al., 2020). The resultant linear association expresses how strong or weak relation exists between them. The coefficient of Pearson’s correlation (r) between two LCFs ‘a’ and ‘b’ is calculated as:

\[
r_{ab} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{a_i - \bar{a}}{\sigma_a}\right) \left(\frac{b_i - \bar{b}}{\sigma_b}\right).
\]  

where \(n\) refers to the size of data points, \(a_i\) and \(b_i\) denote the data points of a and b indexed with i, whereas \(\bar{a}\) and \(\bar{b}\) are the means of observations and standard deviations of data points of variables a and b. The outcomes of the ‘r’ range between –1 (negative correlation) and +1 (positive correlation), while zero value indicate no correlation among two variables (Dormann et al., 2013). However, according to Nettleton (2014), the coefficient values of factors >0.7 represent high collinearity, which can affect the model performance and should be eliminated before data modelling.

**4.1.2 | Factors contribution analysis**

The landslides and their contributing factors vary from area to area depending on local geo-environmental conditions (Hong et al., 2020). Therefore, evaluating the role of different LCFs in terms of their importance for landslide occurrence will help to enhance the predictive...
capability of susceptibility models. For this purpose, the gain ratio and relief-F methods were applied in this study to estimate the relative importance of each conditioning factor in triggering landslides.

Gain Ratio is a well-known feature selection technique used to explore the most important attributes in a dataset that render maximum information about a class. In landslide-related studies, the contribution of each LCF is derived by finding the average merit (AM) values against corresponding factors. The highest AM scores represent the most relevant LCFs and vice versa. However, a factor is regarded as irrelevant, if the AM values are \( \leq 0 \) (Fallah-Zazuli et al., 2019). The gain ratio (GR) for a given LCF is computed as follows:

\[
GR(A) = \frac{IG(A)}{EA(A)},
\]

where \( IG(A) \) and \( EA(A) \) are the information gain and entropy values with respect to an attribute ‘A’. The function \( EA(A) = \sum_i -P(s_i) \log_2 P(s_i) \); where \( P(s_i) \) indicates the probability score of \( i \)th class by contributing to overall scores of attribute ‘A’ classes. The IG function of a given attribute ‘A’ with respect to class ‘X’ is calculated in Equation (6).

\[
\text{Info Gain}(A) = H(X) - H_a(X),
\]

where \( H(X) \) represents the class ‘X’ entropy and \( H_a(X) \) is an average entropy of attribute ‘A’ with respect to class ‘X’ and is computed using Equations (7) and (8), respectively:

\[
H(X) = \sum_i -P(s_i) \log_2 P(s_i),
\]

\[
H_a(X) = \sum_{j=1}^m P_j H(X),
\]

in Equation (7), \( P(s_j) \) is probability score of \( j \)th class corresponding to overall scores. Whereas in Equation (8), \( m \) represents the total number of class partitions, \( P_j \) is the probability score of \( j \)th partition (Quinlan, 1993).

Relief-F is primarily used as a data pre-processing technique that computes the quality and relevance of conditioning factor in a multiclass dataset based on correlation between predictors and their classes (Urbanowicz et al., 2018). Firstly, the relief-F randomly select an instance of a specific attribute, then look for the \( k \)-nearest neighbours of same and different classes of selected instance termed as hits and misses, respectively. Finally, the rank of each predictor is evaluated by averaging the probability weights of all hits and misses (Kononenko, 1994). The computed scores of attributes in a given data generally range between \(-1\) (least significant) and \(+1\) (most significant) (Kira & Rendell, 1992), however in landslide studies, if the factor contribution is equal to 0 or <0, then it is considered as a redundant factor and must be ignored in susceptibility modelling (Ali et al., 2021).

4.2 Landslide susceptibility models

In this study, we have selected six popular models comprising AHP, IoE, WoE, ANN, SVM and LR for predicting the landslide susceptibility of the study area. The working mechanisms of these models are briefly described in the following subsections.

4.2.1 Heuristic model

AHP is the only heuristic approach we employed for the production of landslide susceptibility map. It is a well-known semi-qualitative method that involves expert-based judgements to compute the criteria weights.
of different contributing variables through relative pairwise comparison (Franek & Kresta, 2014; Saaty, 1990). The method has been successfully applied in various studies related to susceptibility mapping for landslides hazard assessments (Bera et al., 2019; Huang et al., 2020; Park et al., 2013; Shahabi et al., 2014; Yalcin et al., 2011). In our case, the practical framework adopted for computing weights of factor and their classes through AHP comprises four stages (i) hierarchic arrangement of causative factors, (ii) pairwise comparative judgement (expert opinion) based on relative importance of factors using rating scale (1–9 and its reciprocal), (iii) weight estimation of each parameter and its classes by computing the principal eigenvector, and (iv) consistency checking to eliminate redundant judgements through consistency ratio (CR), which should be <0.10 (Saaty, 1990).

The CR was calculated as the ratio of the consistency index (CI) and random inconsistency index (RI). Here CI is defined as:

\[ CI = \frac{\lambda_{\text{max}} - n}{n-1} \]  

(9)

where \( \lambda_{\text{max}} \) and \( n \) indicate the largest eigenvalue and the total number of factors/classes in a given matrix, respectively. Whereas RI values were adopted from simulated average CI values of pairwise matrix specified by Saaty (1990) and Franek and Kresta (2014). Finally, the landslide susceptibility index (LSI) was produced in accordance with weighted summation procedure using the following equation (Bera et al., 2019):

\[ \text{LSI}_{\text{AHP}} = \sum_{k=1}^{n} W_k W_{j_k}. \]  

(10)

here \( W_k \) denotes the weight value of LCF \( k \); \( W_{j_k} \) is \( j \)th class weight of factor \( k \) and \( n \) is total number of conditioning factors.

4.3 Statistical models

The statistical models can assist in predicting the susceptibility of landslide through various statistical operations by interpreting a relationship of landslide distribution with their causative variables in a given area (Huang et al., 2020). To comprehend the statistical approach for landslide susceptibility assessment in the study area, we utilized WoE and IoE models.

4.3.1 Weight of evidence

The WoE is a well-established and reliable geo-statistical technique evolved from information and Bayesian theory and is considered as an effective tool for assessment of landslide hazard (Saha & Saha, 2020). The core concept of WoE in landslide susceptibility modelling is to predict the likelihood of landslide occurrence under the same conditions by establishing a relationship between dependent (LCFs) and independent variables (presence and absence of landslide events; Ding et al., 2017). To achieve this target, firstly we calculated positive (\( W^+ \)) and negative (\( W^- \)) weight scores for each class of LCFs using the following equations (W. Chen et al., 2019):

\[ W^+ = \log \frac{P(\text{CF}|\text{LS})}{P(\text{CF}|\overline{\text{LS}})}, \]  

(11)

\[ W^- = \log \frac{P(\text{CF}|\text{LS})}{P(\text{CF}|\overline{\text{LS}})}. \]  

(12)

here \( P \) is the probability; CF and \( \overline{\text{CF}} \) indicate the presence and absence of respective causative factor; \( \text{LS} \) is the presence of landslide events and \( \overline{\text{LS}} \) is the absence of landslide events. Afterwards, the weight scores of \( W^+ \) were subtracted from \( W^- \) to find the weight contrast (\( \Delta W \)) of each class of LCF, which represents the spatial relationship of landslide events with classes of different causative factors. Finally, the LSI was calculated by the summation procedure using Equation (13).

\[ \text{LSI}_{\text{WoE}} = \sum_{i=1}^{k} W_{j_k}^{\text{WoE}}. \]  

(13)

where, \( W_{j_k}^{\text{WoE}} \) is weight contrast score for \( j \)th class of factor \( i \) and \( k \) representing total LCFs (Regmi et al., 2014).

Index of entropy

The index of entropy is a bivariate statistical approach, successfully utilized by various investigators in the assessment of landslide susceptibility by measuring the extent of various causative factors (Q. Wang et al., 2016). In landslide susceptibility modelling, IoE helps to estimate the weight values of each LCF influencing the occurrence of landslide using the following equations:

\[ P_j = \frac{L_j}{D_p}, \]  

(14)

\[ (P_j) = \frac{P_j}{\sum_{i=1}^{n} P_i}, \]  

(15)

where \( L_j \) is landslide percentage and \( D_p \) represents domain percentage; \( (P_j) \) denotes probability density; \( S_j \) indicates the number of classes. Whereas \( H_j \) and \( H_{\text{max}} \) are the entropy values and they are expressed as:

\[ H_j = -\sum_{j=1}^{n} (P_j) \log_2 (P_j), j = 1,...,n. \]  

(16)

\[ H_{\text{max}} = \log_2 S_j. \]  

(17)

\[ l_j = \frac{H_{\text{max}} - H_j}{H_{\text{max}}}, j = 0, 1, j = 1,...,n. \]  

(18)

\[ W_j = l_j \times P_j. \]  

(19)

Here in Equation (18), \( l_j \) is the information coefficient, whereas \( W_j \) is the resultant weight values of each contributing
factor in Equation (19) (Hong et al., 2017; Liu & Duan, 2018). Finally, the LSIIoE using IoE model was prepared from the following equation:

\[ \text{LSIIoE} = \sum_{i=1}^{C} m_i \times C \times W_j, \]  

(20)

where \( i \) is the total number of LCFs used in mapping; the greatest number of classes denoted by \( Z \); \( m_i \) represent the number of classes within a specific LCF; \( C \) is the secondary classified value of each class, whereas the \( W_j \) was obtained from Equation (19) (Q. Wang et al., 2016).

### 4.3.2 Machine learning models

The ML methods are well-understood statistical algorithms, efficiently explored in multiple disciplines to solve the complexity of big data for making accurate predictions in contrast to traditional modelling techniques (Merghadi et al., 2020). In recent years, ML techniques have been extensively used to predict the susceptibility of landslides in various geo-environmental conditions with a significant level of predictive accuracy. In the present case study, three popular ML approaches, that is, MLP, SVM and BLR were adopted to assess the landslide susceptible zones.

**Multi-layer perceptron**

The MLP is a well-known class of feed-forward neural network that uses a supervised learning algorithm to identify complex non-linear associations between predicting variables and response variables (Taud & Mas, 2018). The typical structure of MLP model consists of input/visible layer, hidden layer and output layer interconnected with each other through a set of neurons. The neurons present in theses layers are connected by corresponding weights, which are trained to generate the desired output using activation function.

![Correlation chart of causative factors based on Pearson's correlation matrix](image)

**TABLE 4** Result indicating collinearity diagnostic of landslide causative factors using variance inflation factor

| Sr. no. | Factor                        | Tolerance | Variance inflation factor (VIF) | Sr. no. | Factor                        | Tolerance | VIF  |
|--------|-------------------------------|-----------|--------------------------------|--------|-------------------------------|-----------|------|
| 1      | Aspect                        | 0.749     | 1.336                          | 8      | Precipitation                 | 0.781     | 1.281|
| 2      | Curvature                     | 0.975     | 1.026                          | 9      | Topographic wetness index     | 0.862     | 1.160|
| 3      | Relative relief               | 0.508     | 1.967                          | 10     | Slope angle                   | 0.878     | 1.139|
| 4      | Landuse                       | 0.657     | 1.523                          | 11     | Drainage                      | 0.768     | 1.302|
| 5      | Lineaments                    | 0.550     | 1.820                          | 12     | Roads                         | 0.699     | 1.431|
| 6      | Lithology                     | 0.684     | 1.463                          | 13     | Fault                         | 0.685     | 1.459|
| 7      | Normalized Difference Vegetation Index | 0.556 | 1.799                          |        |                               |           |      |
In this study, we have implemented a single hidden layer MLP neural network to recognize the likelihood of landslide occurrences with respect to input LCFs. The schematic approach of this hierarchical structure is illustrated in Figure 6. The learning parameters (epochs = 821, learning rate = 0.3) and activation function (sigmoidal) were calibrated according to Tien Bui et al. (2016). Support vector machine SVM is widely accepted as a robust predictive model in ML algorithms primarily used to solve classification problems. The core concept of SVM is to maximize the margin between classes and to segregate data points into different classes by establishing a suitable decision boundary or optimal hyperplane (Wu et al., 2008). In studies related to landslide susceptibility, it has been observed that the predictive performance of SVM model is better than other conventional techniques, however, the accuracy is associated with applied kernel function and other tuning parameters (T. Zhang et al., 2018). The radial base function (RBF) is proven to be an effective kernel function in LSP; therefore, RBF kernel was used in this study and can be expressed as follows:

\[
RBF : K(x, y) = \exp\left\{-\gamma \|x - y\|^2\right\},
\]

where, \(K\) is kernel function; \(x\) and \(y\) are input vectors of landslide training data and \(\gamma\) is kernel parameter whose values range between 0 and 1 (Saha & Saha, 2020). The optimum values of tuning or hyperparameters such as C-regularization, kernel coefficient (\(\gamma\)) and loss function (\(\epsilon\)) were adopted from (Merghadi et al., 2020). Afterwards, these parameters were employed in SVM algorithm using a training dataset of normalized LCFs to model the susceptibility of landslides in this study.

Binary logistic regression
BLR is considered as one of the most appropriate predictive ML algorithms used for classification of two-class dataset. It computes the probability of any event by establishing a relation between one target binary variable and several predictors or independent variables (Lever et al., 2016). In this study, we used the presence (1) or absence (0) of landslides as target or dependent variable (\(y\)) and the LCFS as independent variable to map the probability \(P\) of landslide occurrence under the given conditions. Mathematically, the BLR model can be formulated as follows:

\[
P_{BLR} = \frac{1}{1 + e^{-\gamma}},
\]

where, \(\gamma = \alpha_0 + \alpha_1x_1 + \alpha_2x_2 + \ldots + \alpha_nx_n\).

\[
y = \alpha_0 + \alpha_1x_1 + \alpha_2x_2 + \ldots + \alpha_nx_n,
\]
| Factor Classes | Weight | Factor Classes | Weight |
|----------------|--------|----------------|--------|
| Lithology      |        | Proximity to fault (m) |        |
| Alluvium       | 0.026  | 0.23            | 0–250  | 0.445  | 0.168 |
| Murree Formation | 0.278 |                | 250–500 | 0.262 |
| Patala Formation | 0.037 |                | 500–750 | 0.152 |
| Lockhart Limestone | 0.032 |                | 750–1000 | 0.089 |
| Hangu Formation | 0.037  |                | >1000  | 0.052  |
| Panjal Meta-sediments | 0.074 |                |        |        |
| Panjal Volcanics | 0.104 | Lineament density | 0–0.45 | 0.058  | 0.045 |
| Jura Granite     | 0.066  |                | 0.45–0.9 | 0.09 |
| Muzaffarabad Formation | 0.212 |                | 0.9–1.35 | 0.156 |
| Hazara Formation | 0.003  |                | 1.35–1.9 | 0.256 |
| Salkhala Formation | 0.131 |                | 1.9–3.5 | 0.44 |
| Consistency ratio  | 0.07  |                |        |        |
| Slope angle (°) |        | Aspect         |        |
| 0–10            | 0.034  | 0.139          | Flat   | 0.024  | 0.019 |
| 10–20           | 0.049  |                | North  | 0.038  |
| 20–30           | 0.075  |                | Northeast | 0.06 |
| 30–40           | 0.104  |                | East   | 0.087  |
| 40–50           | 0.189  |                | Southeast | 0.266 |
| 50–60           | 0.332  |                | South  | 0.183  |
| >60             | 0.217  |                | Southwest | 0.216 |
| Consistency ratio  | 0.032 |                | West   | 0.095  |
| Curvature       |        | Topographic wetness index |        |
| Concave         | 0.592  | 0.016          | Barren | 0.525  | 0.055 |
| Flat            | 0.075  |                | Forest | 0.111  |
| Convex          | 0.333  |                | Grass land | 0.233 |
| Consistency ratio  | 0.015 |                | Settlements | 0.1 |
| Relative relief (m) |        | Landuse         |        |
| <1000           | 0.53   | 0.034          | Barren | 0.525  | 0.055 |
| 1000–1500       | 0.226  |                | Forest | 0.111  |
| 1500–2000       | 0.151  |                | Grass land | 0.233 |
| 2000–2500       | 0.058  |                | Settlements | 0.1 |
| >2500           | 0.035  |                | Water  | 0.031  |
| Consistency ratio  | 0.085 |                |        |        |
| Proximity to drainage (m) |        | Precipitation (mm) |        |
| 0–100           | 0.37   | 0.077          | <1000  | 0.09   | 0.068 |
| 100–200         | 0.345  |                | 1000–1200 | 0.143 |
| 200–300         | 0.185  |                | 1200–1400 | 0.362 |
| >300            | 0.1    |                | >1400  | 0.406  |
| Consistency ratio  | 0.004 |                |        |        |
| Proximity to road (m) |        | Normalized Difference Vegetation Index |        |
| 0–100           | 0.467  | 0.09           | >15%   | 0.088  | 0.029 |
| 100–200         | 0.277  |                | 15%–30% | 0.243 |
| 200–300         | 0.16   |                | >30%   | 0.669  |
| >300            | 0.095  |                |        |        |
| Consistency ratio  | 0.01  |                |        |        |
| Consistency ratio  | 0.007 |                |        |        |
where $\alpha_0$ is the intercept of the model; $\alpha_1, \alpha_2, \ldots, \alpha_n$ are the regression coefficients and $x_1, x_2, \ldots, x_n$ are the independent variables (LCFs) (Huang et al., 2020).

4.4 | Model validation and comparison

The evaluation of landslide prediction models is a core part of landslide susceptibility mapping for achieving an effective model performance and to ensure the scientific significance of the models used. The validation of these models is commonly assessed through several evaluation metrics like area under operating characteristics (AU-ROC) curve, cross-validation, confusion matrix, root mean squared error, etc. (Frattini et al., 2010). In this study, we use AU-ROC curve, Matthew’s correlation coefficient (MCC), Cohen’s Kappa ($k$) coefficient, accuracy (ACC), $F$-score and confusion matrix fourfold-plot to evaluate the model’s accuracy and to discriminate among resultant models based on their performance scores. The AU-ROC curve was constructed by plotting sensitivity on horizontal axis and 1-specificity on the vertical axis for both training and validation data, whereas the quantitative estimation of AU-ROC values was used to assess model quality; <0.6 indicates poor results, >0.8 represents very good results (Huang et al., 2020; Pourghasemi & Rahmati, 2018). The confusion matrix is kind of contingency table comprising two rows and columns representing predicted values against actual values of both positive and negative landslide counts. This confusion matrix was also used to extract other important evaluation metrics such as ACC, $F$-score and MCC, which can be useful for assessing the robustness of applied models. The formulas for these evaluation indicators are as follows:

\[
\text{Sensitivity} = \frac{TP}{TP + FN},
\]

\[
1 - \text{Specificity} = \frac{FP}{TN + FP},
\]

\[
\text{AUROC} = \frac{\sum TP + \sum TN}{P + N},
\]

\[
\text{Accuracy} = \frac{TP + TN}{TN + FN + TP + FP},
\]

\[
F\text{-score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}},
\]

\[
\text{MCC} = \frac{(TP \cdot TN) - (FP \cdot FN)}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}},
\]
| Factors                        | Classes                  | Domain pixels | Landslide pixels | $W^c$ | $P_{ij}$ | $H_j$ | $H_{jmax}$ | $l_j$ | $w_j$ |
|-------------------------------|--------------------------|---------------|------------------|-------|---------|-------|------------|-------|-------|
| Lithology                     | Alluvium                 | 75,201        | 266              | -2.504 | 0.065   | 2.626 | 3.459      | 0.24  | 0.363 |
|                              | Murree Formation         | 721,390       | 26,400           | -0.151 | 0.048   |       |            |       |       |
|                              | Patala Formation         | 3,442         | 101              | -0.323 | 0.044   |       |            |       |       |
|                              | Lockhart limestone       | 11,535        | 173              | -1.013 | 0.022   |       |            |       |       |
|                              | Hangu Formation          | 3504          | 34               | -1.451 | 0.014   |       |            |       |       |
|                              | Panjal meta-sediments    | 8279          | 742              | 0.863  | 0.134   |       |            |       |       |
|                              | Panjal volcanics         | 27,893        | 4699             | 1.631  | 0.253   |       |            |       |       |
|                              | Jura Granite             | 329,114       | 3605             | -1.48  | 0.016   |       |            |       |       |
|                              | Muzaffarabad Formation   | 72,495        | 16,713           | 2.195  | 0.346   |       |            |       |       |
|                              | Hazara Formation         | 4376          | 10               | -2.905 | 0       |       |            |       |       |
|                              | Salkhala Formation       | 583,513       | 21,056           | -0.156 | 0.054   |       |            |       |       |
| Proximity to fault (m)        | 0–250                    | 75,172        | 7104             | 0.977  | 0.253   | 2.214 | 2.321      | 0.046 | 0.086 |
|                              | 250–500                  | 58,350        | 6607             | 1.181  | 0.303   |       |            |       |       |
|                              | 500–750                  | 43,078        | 3263             | 0.696  | 0.203   |       |            |       |       |
|                              | 750–1000                 | 37,667        | 2102             | 0.355  | 0.149   |       |            |       |       |
|                              | >1000                    | 1,626,475     | 54,723           | -1.032 | 0.09    |       |            |       |       |
| Slope (°)                     | 0–10                     | 86,272        | 818              | -1.511 | 0.033   | 2.615 | 2.807      | 0.068 | 0.069 |
|                              | 10–20                    | 180,877       | 3616             | -0.772 | 0.07    |       |            |       |       |
|                              | 20–30                    | 411,071       | 12,889           | -0.318 | 0.11    |       |            |       |       |
|                              | 30–40                    | 686,169       | 29,565           | 0.122  | 0.151   |       |            |       |       |
|                              | 40–50                    | 390,058       | 21,270           | 0.428  | 0.191   |       |            |       |       |
|                              | 50–60                    | 73,859        | 4897             | 0.559  | 0.232   |       |            |       |       |
|                              | > 60                     | 12,436        | 744              | 0.424  | 0.21    |       |            |       |       |
| Aspect                        | Flat                     | 1202          | 3                | -2.815 | 0.007   | 2.946 | 3.169      | 0.07  | 0.062 |
|                              | North                    | 235,960       | 5626             | -0.596 | 0.075   |       |            |       |       |
|                              | Northeast                 | 218,111       | 8211             | -0.074 | 0.118   |       |            |       |       |
|                              | East                      | 247,603       | 9981             | 0.006  | 0.126   |       |            |       |       |
|                              | Southeast                 | 297,871       | 15,948           | 0.373  | 0.168   |       |            |       |       |
|                              | South                     | 225,774       | 11,637           | 0.305  | 0.162   |       |            |       |       |
|                              | Southwest                 | 215,073       | 11,426           | 0.34   | 0.167   |       |            |       |       |
|                              | West                      | 199,845       | 8262             | 0.035  | 0.13    |       |            |       |       |
|                              | Northwest                 | 199,303       | 2705             | -1.191 | 0.042   |       |            |       |       |
| Curvature                     | Concave                   | 779,455       | 34,895           | 0.208  | 0.376   | 1.578 | 1.584      | 0.003 | 0.003 |
|                              | Flat                      | 287,075       | 10,842           | -0.073 | 0.317   |       |            |       |       |
|                              | Convex                    | 774,212       | 28,062           | -0.175 | 0.305   |       |            |       |       |
| Relative relief (m)           | <1000                    | 265,155       | 26,561           | 1.281  | 0.602   | 1.399 | 2.321      | 0.397 | 0.329 |
|                              | 1000–1500                 | 803,853       | 40,051           | 0.443  | 0.299   |       |            |       |       |
|                              | 1500–2000                 | 584,257       | 6360             | -1.639 | 0.065   |       |            |       |       |
|                              | 2000–2500                 | 175,944       | 818              | -2.283 | 0.027   |       |            |       |       |
|                              | >2500                    | 11,533        | 9                | -3.985 | 0.004   |       |            |       |       |
| Topographic wetness index     | 1–5                      | 1,059,972     | 38,798           | -0.211 | 0.295   | 1.579 | 1.584      | 0.003 | 0.003 |
|                              | 5–9                      | 708,662       | 31,975           | 0.208  | 0.364   |       |            |       |       |
|                              | 9–23.2                   | 72,108        | 3026             | 0.049  | 0.339   |       |            |       |       |
| Proximity to drainage         | 0–100                    | 479,148       | 26,111           | 0.462  | 0.328   | 1.926 | 2        | 0.036 | 0.038 |
|                              | 100–200                   | 417,118       | 21,224           | 0.335  | 0.306   |       |            |       |       |
|                              | 200–300                   | 343,918       | 13,281           | -0.047 | 0.232   |       |            |       |       |

(Continues)
here $P$ and $N$ represent the total number of landslides and non-landslide counts, respectively; $TP$ (true positive) and $TN$ (true negative) are correctly classified pixel counts; and $FP$ (false positive) and $FN$ (false negative) are incorrectly classified pixel counts (Achour & Pourghasemi, 2020; W. Chen et al., 2021). The performance values for LSP models evaluated by $F$-score and accuracy vary from 0 to 1 (values close to 1 indicate as high predictive models and vice versa), whereas the maximum and minimum values of MCC range between $+1$ (best) and $-1$ (worst), respectively (H. Wang et al., 2021).

The Cohen's Kappa coefficient measures the degree of agreement between observed ($P_{\text{obs}}$) and expected ($P_{\text{exp}}$) outcomes using the following expression:

$$K = \frac{P_{\text{obs}} - P_{\text{exp}}}{1 - P_{\text{exp}}}$$  \hspace{1cm} (30)

where $P_{\text{obs}}$ and $P_{\text{exp}}$ are computed by the following equations:

$$P_{\text{obs}} = \frac{TP + TN}{T}$$  \hspace{1cm} (31)

$$P_{\text{exp}} = \frac{(TP + FN)(TP + FP) + (FP + TN)(FN + TN)}{\sqrt{T}}$$  \hspace{1cm} (32)

here $T$ is the total pixels used in training; $n$ is the percentage of correctly classified pixels (Ali et al., 2021). The $K$ values range between 0 and 1. The values close to 0 represent a random agreement, 0.21–0.40 indicates fair agreement, 0.41–0.60 imply a moderate agreement, 0.61–0.80 shows substantial agreement, whereas values >0.80 demonstrate a strong level of agreement (Cohen, 1960).

## 5 | RESULTS

### 5.1 | Collinearity analysis

In the case of landslide susceptibility modelling, the assessment of collinearity is important to diagnose unnecessary variables that may lead to decreased predictive performance of resultant models. For this purpose, Pearson’s correlation and VIF tests were performed to assess the degree of linear association among 13 LCFs. The results of Pearson’s correlation (all <0.7) indicate that all conditioning factors have low degree of association between them (Figure 7). Similarly, the highest value of VIF is quite less than the threshold limit, that is, 5, (Y. Wang, Fang, et al., 2020) indicating no collinearity issue among all LCFs (Table 4). Therefore, the present analysis suggests that all 13 predictors are suitable for susceptibility modelling in this study.

### 5.2 | Factor contribution analysis

Evaluating the relative contribution of causative factors on the occurrence of landslide is an important task because it helps to...
FIGURE 10  Landslide susceptibility maps generated by statistical models (a) weight of evidence (b) index of entropy
detect the most significant predictors for efficient landslide susceptibility modelling. In the present work, GR and relief-F methods were implemented to perform this task. The calculated GR values for all 13 LCFs show that lithology (0.124), landuse (0.110) and slope angle (0.084) are the dominant contributory factors, while the lowest AM scores of TWI (0.009) and curvature (0.007) are within critical limit, therefore all factors were taken into consideration for LSP (Figure 8a). Likewise, the obtained importance using relief-F indicates that among 13 LCFs slope angle (0.0877), landuse (0.0837), precipitation (0.0753) and lithology (0.0456) are the top most important factors, whereas TWI (0.0153), aspect (0.0130) and curvature (0.0055) are the least important factors in landslide probability modelling (Figure 8b).

5.3 | Landslide susceptibility maps

The spatial prediction of landslide in the study area was explored by three different approaches, that is, heuristic (AHP model), statistical (WoE and IoE models) and machine learning (MLP, SVM and BLR models) to produce LSMs using 13 landslide conditioning factors.

5.3.1 | LSP using heuristic model

The class-wise weights of each LCF in AHP analysis were computed through pairwise relative comparison matrix using knowledge-driven approach based on extensive field studies. The result of this comparison
matrix represents a reasonable consistency with values <0.10 for all instances, therefore the calculated class weights of all 13 parameters seem to be more realistic (Table 5). Similarly, the factor weights of all 13 LCFs were evaluated by adopting the same technique. The CR for this analysis is 0.07 showing an acceptable level of consistency which implies that the calculated factor weights are reliable for predicting the heuristic landslide susceptibility model. The final result of class weights and factor weights of 13 LCFs were used in Equation \( (10) \) to produce \( LSI_{\text{WoE}} \) for the target area. The predicted LSI was reclassified into five classes using natural breaks classifier in GIS to produce LSM representing very low (22.2%), low (26.3%), moderate (26.7%), high (17.6%) and very high (7.2%) susceptible zones (Figures 9 and 11). On the other hand, qualitative analysis of actual landslides in each susceptibility class indicates that the maximum percentage of landslide pixels lies in high to very high susceptible zones (Figure 11).

### 5.3.2 | LSP using statistical models

The WoE and IoE models were used as statistical approaches to compute class weights of each thematic layer by analysing a spatial relationship between landslide training dataset as dependent variable and all LCFs as independent variables (Table 6). The above analysis suggests that lithology, landuse, relative relief, proximity to faults, lineament density and slope are the most significant conditioning factors in triggering landslides, whereas the Muzaffarabad Formation, barren lands, moderate relative relief, areas within 500 m of faults, high lineament density and relatively higher slopes (40°–60°), are major factor classes influencing the susceptibility of landslide occurrence in the study area.

The resultant LSIs for both statistical models were constructed by applying prediction scores in Equations \( (13) \) and \( (20) \) using summation procedure in ArcGIS environment. These LSIs were then reclassified into five susceptible classes, that is, very low (VL), low (L), moderate (M), high (H) and very high (VH) using widely used Jenks classification scheme (W. Chen et al., 2021; Merghadi et al., 2020) to produce final LSMs of the study area (Figure 10). The class-wise area percentage distribution of landslide susceptible zones (LSZs) indicates that 75% area occupies VL to M zones, while the remaining 25% area falls in H to VH susceptible zones in WoE model. On the other hand, IoE model has slight changes in area percentage, that is, 77% in VL to M and 23% in H to VH susceptible zones (Figure 11). Furthermore, the
distribution of existing landslide pixels in each susceptibility class depicts that most landslide counts can be observed in H to VH susceptible zones of both statistical LSMS, representing a reliable prediction result (Figure 11).

5.3.3 | LSP using machine learning models

In this article, three standalone machine learning algorithms (MLP, SVM and BLR) were implemented in Weka 3.8.4 software to compute prediction scores of training dataset, which were then processed in GIS to build pixel-based LSIs of the entire study area. The resultant LSI of each model was reclassified into very low, low, medium, high and very high susceptible zones based on Jenks classifier to generate the map of landslide susceptible areas (Figure 12). According to all LSMS, the higher susceptibility can be observed along Neelum Highway, proximity to main faults and areas bordering Neelum River and its feeding tributaries, especially along the steep valley slopes in the central and western portions of study area. Overall, the relative area percentage, existing landslides distribution and their frequency ratio in each susceptible class of resultant LSMS are summarized in Figure 11. These results reveal that the area-based percentage of H to

FIGURE 13  Receiver operating characteristics curves of all six models (a) training dataset; (b) validation dataset
VH zones in all three ML models, that is, BLR (26.2%), SVM (25.2%) and MLP (25.3%) have almost similar proportion, whereas BLR (57.2%) gained higher proportion in VL to L susceptible classes as compared with SVM (47.8%) and MLP (46.4%) in the study area. Moreover, the frequency ratio analysis of past landslides in each susceptibility class reflects that maximum concentration of landslides was noticed in high to very high zones of all produced LSMs.

5.4 Model performance and comparison

The performance of each model employed in this study was assessed by examining the spatial concordance of actual data of landslide and non-landslide with the prediction results of each model using the application of several validation methods, that is, AU-ROC, ACC, F-score, MCC, Kappa and confusion matrices (Figures 13 and 14). The training dataset was utilized to compute the performance of each model in terms of their success rate, whereas the predictive ability of derived LSP models was evaluated by using the testing dataset of observed landslides and non-landslides.

According to the results, respective AU-ROC values of 0.881, 0.860, 0.842, 0.810 and 0.802 for BLR, MLP, SVM, IoE and WoE models showed that the success rates of LSP models generated by BLR, MLP and SVM were superior as compared with IoE and WoE (Figure 13a). Likewise, the ACC and F-score results of BLR (0.797, 0.787), SVM (0.777, 0.764), MLP (0.773, 0.753), IoE (0.755, 0.739) and WoE (0.741, 0.745) models further validated the superiority of BLR, MLP and SVM over IoE and WoE models.
and WoE (0.741, 0.745) models suggest that BLR model had performed better as compared with others. An identical order was observed in the results yielded by MCC and K coefficient matrices, which implies that BLR (0.609, 0.604) model had gained the highest performance rate followed by SVM (0.561, 0.554), MLP (0.554, 0.547), IoE (0.520, 0.511) and WoE (0.491, 0.489) models (Table 4).

On the other hand, the prediction scores obtained through AU-ROC for all six models indicate a similar tendency with slight variations in results when compared with performance scores of training data. The BLR model achieved highest AU-ROC value of 0.85 followed by MLP (0.84), SVM (0.83), IoE (0.79), WoE (0.78) and AHP (0.74) models (Figure 13b). Whereas, different pattern was observed in the results of ACC and F-score based on testing dataset, that is, SVM (0.770, 0.766), BLR (0.761, 0.764), MLP (0.756, 0.758), IoE (0.756, 0.748), WoE (0.732, 0.740) and AHP (0.723, 0.731). Similarly, the results of MCC and K coefficient matrices showed that the predictive performance of all models lies in good category and has an acceptable level of agreement. The highest and lowest values of these metrics range between 0.554 and 0.450 (Table 7). Furthermore, the contingency plots of all six models illustrating percentages of correctly and incorrectly classified landslide and non-landslide picture elements validate the reliability of employed models in predicting the spatial distribution of landslide in the study area (Figure 14). The overall performance scores comparison of all six models indicates that BLR, MLP and SVM (machine learning models) had significantly higher learning and prediction capabilities than statistical (IoE and WoE) and AHP models, respectively.

6 DISCUSSION

The spatial prediction of landslide susceptibility at various scales provides a foundation for effective landuse planning and hazard management in a complex mountainous landscape (Aditian et al., 2018; Erener & Düzgün, 2012). Due to its unique topographic configuration, tectonic fragility and harsh climatic conditions, the Kashmir Himalaya is considered as a place sensitive for landslide disasters. Being a part of this region, the studied area has faced an enhanced rate of landsliding in recent decades due to the megathrust of 2005 and rapid growth in socio-economic activities, which exacerbate the risk of landslide hazard (Rahman et al., 2014; Sana & Nath, 2017). However, the exploration of LSP models using current practices and their comparison with traditional techniques to evaluate an optimal model for landslide susceptibility assessment is still lacking in this region. To address this issue, we employed and compared widely used data-driven techniques such as machine learning (MLP, SVM and BLR), statistical (WoE and IoE) and heuristic (AHP) to generate LSMS of earthquake-affected road section in a part of western Himalaya in Kashmir.

In general, the LSP modelling is mainly dependent on selection of factors contributing to landslides, as it has a substantial impact on the predictive performance of models. The criteria for the selection of LCFs is still debatable because the variable that influences landslides may vary under different geo-environmental conditions. However, it is important to employ variable selection techniques to maximize the performance of the LSP model by removing noisy factor before the training phase (Merghadi et al., 2020; Reichenbach et al., 2018). To ensure this, Pearson’s correlation and VIF tests were performed, which demonstrates that degree of linear association among all the 13 LCFs lies within the threshold limits specified by Dou et al. (2020) (Figure 7; Table 1). Additionally, the selected LCFs were analysed using GR and relief-F methods to find the contribution of each factor in aiding to initiate landslides. Results revealed that the slope angle, lithology, landuse and precipitation were the most significant factors while curvature, TWI and aspect were the least important factors influencing landslides in the study area (Figure 8). Our findings are in agreement with the previous studies (Basharat et al., 2016; Basharat, Rohn, Baig, & Khan, 2014; Kamp et al., 2008; Rahman et al., 2014), where these factors played a dominant role in the occurrence of landslides. Similarly, the distribution of landslides and their causes inferred from field observations also complement our findings; for instance, fragile lithology on terrain slopes aggravated the phenomena of landsliding when it rains and the rapid and unplanned construction activities also triggered shallow landslides. On the basis of these analyses, 13 LCFs, that is, lithology, proximity to faults, slope angle, aspect, curvature, relative relief, TWI, proximity to drainage, lineaments density, NDVI, landuse, precipitation and proximity to roads were selected in this article to predict landslides susceptibility.

Numerous studies were performed to generate regional-scale LSMS and proposed suitable models for the assessment of susceptibilities. Recently a review highlighted that more than 500 research articles based on 70 different models were published in 2005–2016 (Pourghasemi et al., 2018); however, it is pertinent to mention here that a few studies (Ahmed et al., 2021; Basharat et al., 2016; Kamp et al., 2008) were conducted to generate LSMS of the 2005 earthquake-affected areas of Kashmir Himalayas. Additionally, these investigations have a limited scope in respect of modelling techniques and lack current practices with an integrated approach to demarcate the LSZs. To generate the LSMS of area under investigation, six different data-driven models (AHP, BLR, IoE, MLP, SVM and WoE) were built by utilizing expert opinion and training dataset along with validation dataset. Thus, these models were employed to determine the LSMS of all the pixels and then compared with each other in terms of prediction accuracies and distribution of landslide susceptibility levels in corresponding LSMS to analyse a more accurate LSP model. Previously, Basharat et al. (2016) and Kamp et al. (2008) produced LSMS, which demonstrated the landslide potential zones along the major faults and/or associated with seismic events. Furthermore, Khan et al. (2013) documented landsliding on the basis of 5 years photographic record (2005–2010) in this region and concluded that landscape resumed equilibrium 5 years after earthquake, although the phenomena of landsliding are still ongoing, which has a positive relationship with human activities. We support the findings of Khan et al. (2013) that earthquake-triggered landslides became stable and/or exhausted in 2010, while in recent years a large number of new landslides occurred or reactivation of existing landslides is observed, which could be the result of intense rainfalls, erosion by the Neelum River.
and most influentially by rapid and unplanned increase in slope cutting for socio-economic activities. Considering new landslides (2010–2020) in addition to the pre-existing landslides data along targeted road section, our LSMs predicted the landslide potential zones with a high rate of predictive accuracy as compared with previous studies. The generated LSMs of all six models are well harmonized with one another, although the ratio of LSZs with respect to area percentage distribution is different in each model (Figure 11). Generally, a uniform pattern of high and very high LSZs in all models observed along an earthquake-affected road section of Neelum Highway; however, it was noticed in field investigations that landsliding is the most common phenomenon with potential hazards along slope angles ranging from 40° to 60° and fragile lithologies that lies in the proximity to faults, roads and drainages. On the other side, the low and very low LSZs are mainly dispersed in the areas with slope angles less than 20°, far from roads and drainage networks, away from faults and less affected by anthropogenic activities. In general, the ML models, i.e., BLR, MLP and SVM predicted well with respect to observed landslide percentages of 75.0%, 73.04% and 72.79% for high and very high LSZs in comparison with statistical models (WoE = 70.11%, IoE = 68.54%) and AHP model (69.06%) of area under study (Figure 11).

Furthermore, different accuracy assessment methods, that is, AUROC, ACC, F-score, MCC, Kappa and confusion matrices on testing and training datasets were employed for each model to evaluate/validate the model prediction performance and their comparison. The model with a greater and/or lower success rate and prediction rate can validate and explain how well the model classified the area based on landslide inventory and how well the model predicted the landslide hazards (Pourghasemi & Rahmati, 2018). As a result of these analyses, it can be deduced from the model’s comparison in Section 5.4 that all the six models used in this study have shown a considerable predictive capability to produce LSMs, although the ML models in general have a higher rate of predictive accuracy when compared with other models. In addition to this, the ML algorithms have many benefits in the model processing and relatively simple to interpret without bulk of background information (Achour & Pourghasemi, 2020; H. Wang et al., 2021). Whereas, the other data-driven techniques used in this study need several datasets to train and test each model. Unfortunately, not a single ML technique model was used for landslide susceptibility mapping in the seismically active zone of the studied region. Only Kamp et al. (2008) produced a regional level LSM of 2005 earthquake-affected areas with a prediction accuracy of 67% by using AHP technique, whereas our findings revealed 74% accuracy of landslide prediction by AHP model which has a considerably better degree-of-fit to the assessing data. Overall, tBLR method outperformed the other models and exhibits the highest capability in terms of landslide prediction and LSZs distribution, followed by MLP, SVM, IoE, WoE and AHP model (Figure 13; Table 4).

In the literature, numerous models such as heuristic (AHP), multivariate and bivariate statistical and machine learning, etc., were used for LSP. Each model has its obvious advantages and disadvantages with respect to the data source’s reliability, pre-processing and weighting of causative factors, level of expertise, etc. (Huang et al., 2020). Therefore, assessing the advantages and drawbacks of applied modelling techniques has become more relevant in the framework of landslide susceptibility studies. In this article, the employed heuristic model provides a very flexible and simple decision-making, which can be conveniently accommodated in the GIS domain, while subjective decision-making system is a major drawback of this approach. The WoE and IoE models use recorded landslide cell densities to reveal the geographical connection between landslide incidents and causative variables in the research region. Missing factor data and under-sampled landslide data as inputs have no major influence on the model’s outcomes, which is the model’s main benefit (Ding et al., 2017; Q. Wang et al., 2016). However, these models have disadvantages in measuring the relationship between landslide occurrence and conditioning factors. The ML models are known to have the benefit of being able to handle a wide range of data that are non-symmetric and display complicated known input–unknown output connections, which are prevalent in the natural world due to their flexible and nonlinear properties. The disadvantages of these models are that they require a large number of prior knowledge or assumption and are unable to compute the correlations between sub-classes of LCFs; similarly difficulties in model tuning and over-fitting problems can lead to affect the prediction accuracy (Merghadi et al., 2020). The MLP model was selected in this study as it has better nonlinear mapping ability for performing LSP as compared with commonly used conventional artificial neural network model, and it can affectively work with inaccurate and fuzzy data. The structural parameters in MLP require appropriate tuning such as selection of suitable values of hyper-parameters and number of neurons in hidden layer, which is important to conduct correct susceptibility maps. However, the lack of automated approaches for determining the optimal number of layers or the optimal number of internal parameters required for a given application task, and to optimize the internal structure of a module is still a noticeable issue in this model. The SVM works well in high-dimensional domains with more dimensions than samples. It is memory economical since it only employs a subset of training points (called support vectors) in the decision function. Different kernel functions may be specified for the decision function, making it flexible. When the number of features is substantially more than the number of samples, however the selection of kernel functions and regularization terms is critical to avoid over-fitting. It is unable to offer probability estimates directly; these must be generated through a computationally intensive cross-validation method. The better classification capacity of the BLR model provides a useful estimate on spatial relationship between a given phenomenon and the factors affecting its occurrences, similarly it has the ability to use independent variables that are not normally distributed, and dependent variables that can be continuous, discrete and binary. The most important disadvantage of this method in LSP is the assumption of linearity between the dependent variable and the independent variables or predictors.

Being an important portion of the discussion section, the limitations of the techniques and dataset employed in this study can be summarized as: (i) currently, there are no standards and code of
practices established to map and evaluate the susceptible areas for landslide occurrence. Therefore, it is always a challenge in selection and adoption of an appropriate technique/method for the evaluation of landslide susceptibility, which resulted in an uncertain condition on account of its reliability and credibility of outcomes obtained by the adopted method: (ii) in this study, we focused on an earthquake-affected road section to generate LSMs and to compare their predictive performances. For this, a landslide inventory was prepared by compiling field data and remote sensing data. However, due to the limitations of historical images, we were not able to exactly identify the landslides before the 2005 Kashmir earthquake, particularly of smaller size; (iii) another limitation of this study is that it does not propose the causative mechanism of slope failure due to a complex relationship with triggering factors, thus it can only be employed as an initial step in the assessment of landslide phenomena; (iv) the analysis based on AHP model is one of the limitations, as it strongly relies on the opinion of geologist/expert and it refers to their subjectivity/field knowledge in a specific area; (v) an important problem can be seen because we did not classify landslides by their type of movement in order to generate LSMs and considered each type of landslide occurred by following same processes, whereas the causative factors and triggering factors may vary for different mode of movement; (vi) finally, the last and most important point is that the results obtained for the assumption of landslide hazard zones are only viable for similar geo-environmental conditions. Therefore, the predictions based on present geo-environmental conditions and/or the mechanisms that control the slope failure are not a guarantee for the future, if these conditions change.

To improve the presented methodology of landslide susceptibility zonation, the above-mentioned limitations (i)–(v) must be considered for developing new LSP models. Recently, novel ML and deep learning approaches, as well as their ensembles explored in landslide susceptibility mapping, have had significant prediction accuracies. So, employing these techniques and comparing them with other statistical and multicriteria decision-making methods can help to find an optimal model for LSP in the studied region of Kashmir Himalayas.

7 | CONCLUSIONS

The landslide disasters in an earthquake prone region of Kashmir Himalayas are mainly controlled by combined interaction of multiple geo-environmental and anthropogenic drivers that badly affected the human population in terms of infrastructure deterioration and socioeconomic development. Hence, it is indispensable to assess the critical vulnerable zone of slope failures in this region for emergency management/risk analysis and minimizing oncoming landslide hazards. The present study was focused to analyse landslide susceptibility along a road section of Neelum Highway where natural slopes were severely disturbed by post-earthquake activities. We developed six different LSP models by applying heuristic (AHP), statistical (WoE and IoE) and machine learning (BLR, MLP and SVM) techniques based on site-specific causative factors with detailed landslide inventory and compared their prediction performance to evaluate the robustness of employed models. Our analysis revealed that all the six models show promising results; however, ML models exhibited remarkable LSP in comparison with statistical and heuristic models. The BLR reflected the highest prediction accuracy in the seismogenic zone of Kashmir Himalaya followed by MLP, SVM, WoE, IoE models, while AHP was found to be the least effective method in demarcation of landslide susceptible areas along targeted road section. The performance scores derived through statistical metrics provide a valuable indication that the employed models performed well in predicting spatial representation of landslide susceptibility; however, ML portrays the highest predictive performance, comparatively. The majority of predicted landslides distribution pattern was observed in western and central parts of the study area, particularly in the proximity of road/faults and deeply dissected valley slopes, which replicates the actual situation of slope failures evident from field observation. The analysis of factor contribution in landsliding and field observations suggested that unstable and fragile lithology on steep slopes were dominant contributors in landsliding mainly controlled by climatic and anthropogenic factors. In conclusion, we presumed that the established methods have a reliable capability to predict landslide potential zones, which could assist the local government and decision makers in mitigation and prevention of landslide disasters along the highway road corridors.

AUTHOR CONTRIBUTIONS

Syed Ahsan Hussain Gardezi: Methodology; Analysis and Investigations; Writing original draft. Nadeem Ahmad Usmani: Methodology; Analysis and Investigations; Writing original draft. Xiao-qing Chen: Writing - review and editing; Supervision. Nawaz Ikram: Analysis and Investigations. Writing - review and editing. Sajjad Ahmad: Writing - review and editing. Wani: Analysis and Investigations.

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CONFLICTS OF INTEREST

The authors declare that they have NO known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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Research data are not shared.

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