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# Utilizing Grid Data and Deep Learning for Forest Fire Occurrences and Decision Support: A Case Study in the Ningxia Hui Autonomous Region

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**Abstract:** In order to investigate the geographical distribution of forest fire occurrences in the Ningxia Hui Autonomous Region, this study employs advanced modeling techniques, utilizing diverse data sources, including fuel, Gross Domestic Product (GDP), population, meteorology, buildings, and grid data. This study integrates deep learning Convolutional Neural Networks (CNNs) to predict potential fire incidents. The research findings can be summarized as follows: (i) The employed model exhibits very good performance, achieving an accuracy of 84.35%, a recall of 86.21%, and an Area Under the Curve (AUC) of 87.67%. The application of this model significantly enhances the reliability of the forest fire occurrence model and provides a more precise assessment of its uncertainty. (ii) Spatial analysis shows that the risk of fire occurrence in most areas is low-medium, while high-risk areas are mainly concentrated in Longde County, Jingyuan County, Pengyang County, Xiji County, Yuanzhou District, Tongxin County, Xixia District, and Yinchuan City, which are mostly located in the southern, southeastern, and northwestern regions of Ningxia Hui Autonomous Region, with a total area of 2191.2 square kilometers. This underscores the urgent need to strengthen early warning systems and effective fire prevention and control strategies in these regions. The contributions of this research include the following: (i) The development of a highly accurate and practical provincial-level forest fire occurrence prediction framework based on grid data and deep learning CNN technology. (ii) The execution of a comprehensive forest fire prediction study in the Ningxia Hui Autonomous Region, China, incorporating multi-source data, providing valuable data references, and decision support for forest fire prevention and control. (iii) The initiation of a preliminary systematic investigation and zoning of forest fires in the Ningxia Hui Autonomous Region, along with tailored recommendations for prevention and control measures.

**Keywords:** forest fires; occurrence prediction; Convolutional Neural Networks (CNNs); geographic distribution; multi-source data

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## 1. Introduction

In recent years, forest fires have emerged as an increasingly urgent global issue, with notable incidents occurring worldwide. One such example is the forest fires plaguing the Sumatran forests in Indonesia [1], resulting in devastating environmental consequences. Similarly, in Malaysia, the Raja Musa Forest Reserve (RMFR) also faces recurrent challenges posed by forest fires [2]. Forests have a significant impact on fostering sustainable growth at a regional level, particularly in terms of economic development, while also safeguarding biodiversity [3,4].

Especially in northwest China, scarce forest resources play a huge ecological significance in the regional ecological environment, such as wind and sand control, water conservation, and ecological environment improvement [5]. In regions where urban development meets or intermingles with natural vegetation, known as the Wildland–Urban Interface (WUI) or Wildland–Urban Intermix depending on population density near forests, wildfire prevention and mitigation are critical. The close proximity of forests to urban areas heightens wildfire risks, necessitating strong prediction and control strategies. Wildfires not only threaten forest resources but also significantly affect people's lives and property. Accurate forecasting and proactive preventive measures are thus crucial in the WUI. The goal is to decrease both the occurrence and severity of wildfires in these areas by evaluating specific fire hazard severity zones. This evaluation considers factors such as proximity to vegetation, access difficulties, and local weather conditions that can elevate fire risks. Effective management in these WUI areas is essential to protect both the natural and built environments [6,7].

There are various methods for predicting wildfire occurrence, spanning multiple fields. The primary methods include historical data analysis, Geographic Information System (GIS) technology, meteorological data analysis, remote sensing technology, comprehensive risk assessment, and analysis of socioeconomic factors. These approaches help identify potential wildfire occurrence factors and aid in the development of effective fire prevention strategies [8]. A variety of forest fire occurrence prediction methods have been developed at home and abroad, which are mainly summarized as the following three methods: (i) Experiments based on combustion and fire risk prediction based on historical forest fire data and ignition experiments in the study area to determine the threshold range of forest fire driving factors for combustible materials to reach ignition point [9,10]. (ii) Involving a rigorous statistical examination of the correlation between factors contributing to forest fires and actual recorded forest fire events, this study leverages historical forest fire data to predict the potential occurrence of fire incidents within the context of regional environmental conditions. By analyzing the interplay between various triggering factors and fire incidents, the aim is to enhance our understanding of fire risk within the specific regional context and inform decision-making processes [11,12]. (iii) Using machine learning methods to build occurrence prediction models to train and test forest fire datasets to predict occurrence probabilities [8,13]. However, there is a scarcity of research that combines gridded data with deep learning for predicting forest fire occurrences at the provincial level, despite the fact that gridded data can effectively account for spatial heterogeneity and discern variations within grid cells [14,15]. Convolutional Neural Networks show good performance in predictive learning [16]. Compared to the Internet of things [17–19] and Integrated systems [20], CNN technology offers significant advantages, particularly its automatic feature extraction capability, which reduces reliance on manually designed, complex feature extractors. This enhances adaptability to diverse data types and intricate patterns. Deep learning CNNs have demonstrated exceptional performance in domains such as image recognition, speech recognition, and natural language processing. CNNs efficiently handle large-scale data, delivering real-time predictions at impressive speeds and excelling in tasks requiring extensive image data processing. At the core of CNNs are their convolutional layers, utilizing convolution operations and a sliding window mechanism to capture local features in input data. The weight-sharing mechanism, employing identical convolutional kernels throughout the entire image, reduces network parameters, contributing to the suitability of CNNs for processing extensive image data. In contrast, Conventional Neural Networks (CNNs) lack a distinct local perception mechanism, connecting each neuron in input and hidden layers with every neuron in the following layer. NNs are more suitable for processing one-dimensional data like text or time series data. CNNs typically feature a lower parameter count, simplifying training processes even with limited datasets [21,22].

Ningxia is situated within the sand control belt of northern China and falls within the ecological protection belt of the Silk Road, making it strategically important for China's ecological security [23]. Predicting wildfires in Ningxia is crucial for actively preventing wildfires and protecting the forest resources in the northwest region of China. Therefore, this study focuses on the Ningxia Hui Autonomous Region with the following objectives: (i) Develop an economically efficient and highly accurate method for forecasting future forest fire occurrences using grid data and Convolutional Neural Network (CNN) technology. (ii) Predict and depict the potential forest fire occurrences in Ningxia, providing valuable insights for optimizing forest fire prevention planning in the northwest region. This study aims to achieve these goals and, in the process, contribute to actively protecting ecological resources and mitigating the occurrence of forest fires in this ecologically critical.

## 2. Materials and Methods

### *2.1. The Study Area*

As shown in Figure 1, Ningxia Hui Autonomous Region is situated in the upper reaches of the Yellow River, covering a land area of 6.64 million square kilometers. The region's topography exhibits elevations that are higher in the south and lower in the north. The northern areas are characterized by developed agriculture and abundant vegetation, while the central arid belt consists of gently sloping hills and mountain basins. Moving further south, the terrain becomes increasingly mountainous [24]. The region encounters a temperate continental arid and semi-arid climate characterized by an average annual rainfall of 305 mm and an evaporation rate of 1800 mm. These conditions contribute to limited rainfall, water scarcity, and a delicate ecological environment, posing challenges to both the natural environment and socioeconomic development [25].

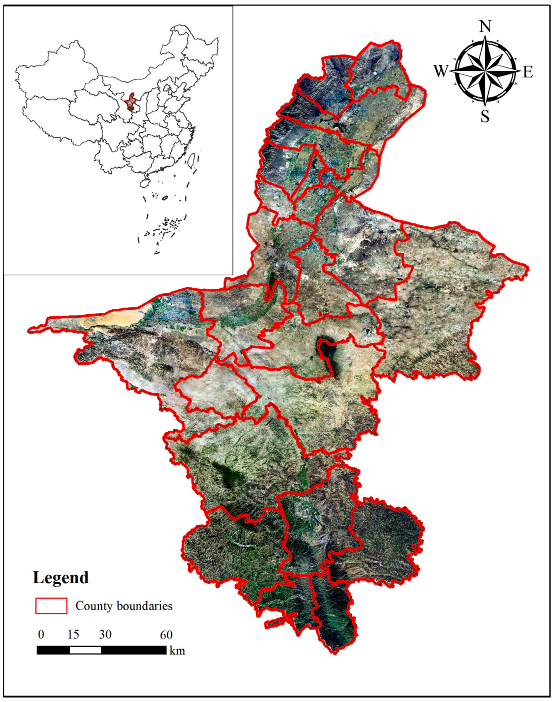


**Figure 1.** Location of study area.

*2.2. Data Source*

In this study, we utilize primary data sources that include fire point data, topographical data, meteorological data, combustible material data, and socioeconomic data, as outlined in Table 1. To assure data consistency and comparability, data preprocessing techniques such as standardization have been applied, thereby enhancing data quality. This refinement enables our model to more accurately discern patterns and relationships within the data, bolstering the reliability of our research and the precision of our model, which provides a robust base for scientific investigation. Fire point data, in particular, elucidates the spatial and temporal distribution and frequency of fires, granting us intuitive insights into fire activities. The topographical data aids in comprehending how terrain features, like elevation and slope, influence fire spread and expansion. Meteorological data informs us of crucial conditions like wind speed, direction, temperature, humidity, and precipitation, all of which are pivotal in the initiation and evolution of fires. Information on the type, distribution, and moisture content of combustible materials helps assess the potential risk and propagation speed of fires.

**Table 1.** The primary data used in this study.

| Sub-Classification | Data | Resolution |
|---|---|---|
| Wildfires point | Forest Fire Points Survey in Ningxia Hui Autonomous Region | - |
| Topographic data | Elevation, Slope, Aspect | 30-arcsecond grid |
| Meteorological data | Average wind speed, average precipitation, average temperature, maximum temperature, minimum relative humidity, hours of sunshine, etc. | 30-arcsecond grid |
| Fuel data | Combustible, Inflammable, Incombustible | 30-arcsecond grid |
| Socioeconomic data | Population, Gross Domestic Product (GDP), the count of buildings, and the building area, among others. | 30-arcsecond grid |

The socioeconomic data details factors such as population density, economic development levels, and the spread of human activities, shedding light on the human impact on fire starts and progress. Human activities, for example, can instigate fires, while economic and social contexts might shape the development of fire management and mitigation strategies. Through a thorough analysis and processing of these datasets, our study uncovers the intricate mechanisms of fire occurrences and development, leading to the proposition of more effective preventative and responsive measures. This is vital not just for safeguarding human life and property but also for maintaining the health and stability of our ecosystems.

2.2.1. Terrain Data

The historical fire points used in this study are the census survey data of Ningxia Hui Autonomous Region, which are from 2000 to 2020, and all of them are confirmed to be historical fire points by county–city–province audit, with 225 points in total, the most in Lunde and Jinyuan counties. The DEM data were obtained from the Center for Resource and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn, accessed on 8 January 2022), and we extracted the slope and slope direction from the DEM, as shown in Figure 2 and Table 2. The areas with high elevation are located in Haiyuan County, Lunde County, Jinyuan County, Xiji County, Panyang County, Concentric County, etc. The districts and counties of Pingluo, Helan, and Jinfeng District are located in the lower elevation districts and counties. Areas with steep slopes are located in the northwestern part of Ningxia Autonomous Region (western part of Helan County, western part of Dawukou District, and western part of Huinong District), Lunde County, Jinyuan County, Xiji County, Pengyang County, etc.

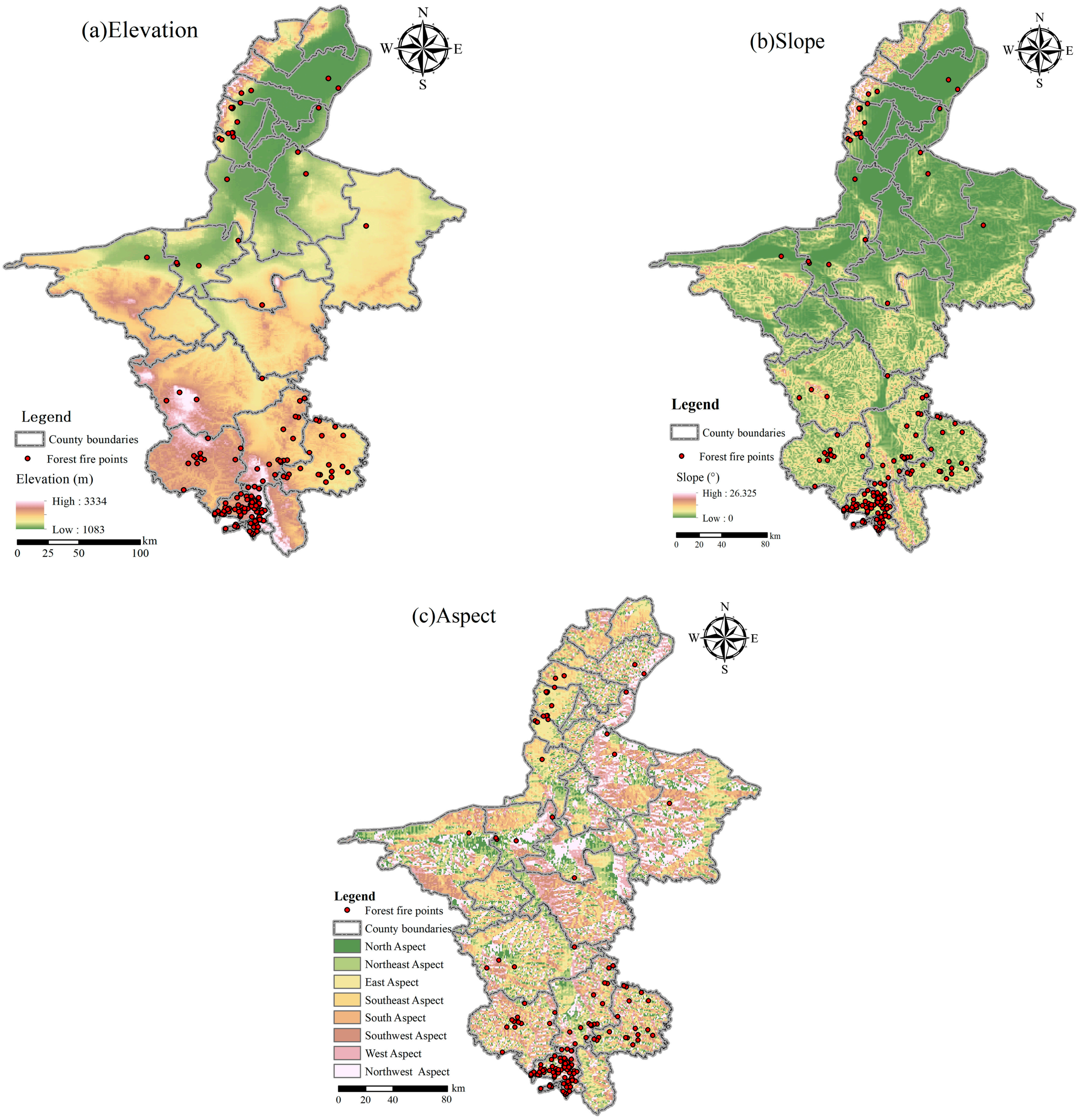


**Figure 2.** Ningxia's topographic data comprises (**a**) elevation, (**b**) slope, and (**c**) aspect information.

**Table 2.** Topographic data information.

| Classification | Data |
|---|---|
| Elevation | Mountainous terrain, Plateau, Plain, and so on. |
| Slope | 0–5° degrees is categorized as gentle slope, 6–15° degrees as moderate slope, 16–25° degrees as steep slope, and 26–35° degrees as steep slope. |
| Aspect | Basic slope orientation classification: In the horizontal direction, it is divided into four cardinal directions, namely east, west, south, and north. In the inclined direction, it is categorized into four directions: southeast, southwest, northeast, and northwest. |

2.2.2. Meteorological Data

As shown in Figure 3 and Table 3, the meteorological data were sourced from the China Daily Ground Climate Data Set. This dataset compiles information from meteorological stations within the Ningxia Hui Autonomous Region. To enhance the accuracy and diagnostic capabilities of our model, we employed ANUSPLIN interpolation, a technique with a well-established track record [26,27]. As part of a comprehensive pre-study [8], we meticulously selected key meteorological parameters, including daily maximum temperature, sunshine hours, average air pressure, daily average relative humidity, maximum wind speed, and average wind speed, among others.

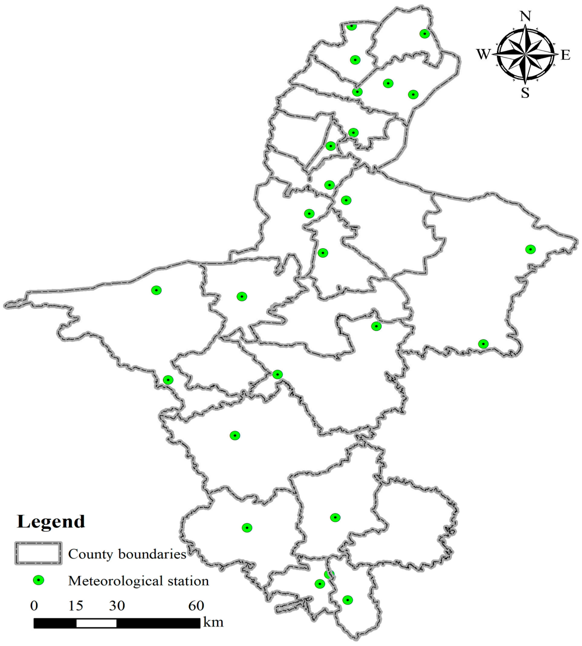


**Figure 3.** Ningxia weather station distribution map.

**Table 3.** Weather condition data table for meteorological stations.

| No | Number of Windy Days Month (Days) | Monthly Average Wind Speed (m/s) | Monthly Average Precipitation (mm) | Monthly Average Temperature (°C) | Monthly Maximum Temperature (°C) | Monthly Minimum Relative Humidity (%) |
|---|---|---|---|---|---|---|
| 1 | 0.01 | 0.90 | 17.2 | 9.7 | 25.1 | 0 |
| 2 | 0.11 | 1.57 | 17.4 | 10.9 | 25.5 | 2 |
| 3 | 0.11 | 1.57 | 17.4 | 10.9 | 25.5 | 2 |
| 4 | 0.11 | 1.57 | 17.4 | 10.9 | 25.5 | 2 |
| 5 | 0.01 | 0.90 | 17.2 | 9.7 | 25.1 | 0 |
| 6 | 0.94 | 2.24 | 17.5 | 9.8 | 25.4 | 2 |
| 7 | 1.44 | 2.12 | 14.8 | 10.5 | 24.3 | 3 |
| 8 | 1.44 | 2.12 | 14.8 | 10.5 | 24.3 | 3 |
| 9 | 1.03 | 2.16 | 16.0 | 9.5 | 24.2 | 3 |
| 10 | 0.27 | 1.76 | 17.4 | 10.1 | 25.0 | 1 |
| 11 | 1.36 | 3.12 | 23.6 | 10.2 | 25.6 | 2 |
| 12 | 1.36 | 3.12 | 23.6 | 10.2 | 25.6 | 2 |
| 13 | 0.28 | 1.99 | 28.1 | 9.1 | 24.0 | 2 |
| 14 | 0.27 | 1.76 | 17.4 | 10.1 | 25.0 | 1 |
| 15 | 0.04 | 1.58 | 38.7 | 6.5 | 20.4 | 0 |

**Table 3.** *Cont.*

| No | Number of Windy Days Month (Days) | Monthly Average Wind Speed (m/s) | Monthly Average Precipitation (mm) | Monthly Average Temperature (°C) | Monthly Maximum Temperature (°C) | Monthly Minimum Relative Humidity (%) |
|---|---|---|---|---|---|---|
| 16 | 0.04 | 1.58 | 38.7 | 6.5 | 20.4 | 0 |
| 17 | 0.51 | 2.28 | 64.2 | 6.6 | 20.5 | 4 |
| 18 | 0.08 | 2.55 | 47.8 | 6.4 | 19.0 | 5 |
| 19 | 0.39 | 1.82 | 45.0 | 8.4 | 23.1 | 3 |
| 20 | 0.38 | 1.99 | 17.7 | 11.2 | 26.2 | 1 |
| 21 | 0.38 | 1.99 | 17.7 | 11.2 | 26.2 | 1 |
| 22 | 0.59 | 2.31 | 37.5 | 8.1 | 21.9 | 0 |

### 2.2.3. Fuel Load

"Fuel Load" plays a crucial role in fire risk analysis, particularly in forested areas. In the Ningxia Autonomous Region, the distribution of these fuels significantly influences the occurrence and spread of fires. As depicted in Figure 4, the distribution of fuels on forested land is evident. Notably, areas with a higher concentration of combustible and flammable materials are primarily located in Yuanzhou District, Longde County, Pengyang County, Tongxin County, Yanchi County, and Helan County. The substantial fuel load in these regions implies that once ignited, fires may spread swiftly, leading to extensive burning. Additionally, other factors might exacerbate fire risk in these locations, such as arid climatic conditions and human activities. To effectively understand and manage fire risks, comprehensive research is essential in these high-fuel-load areas.

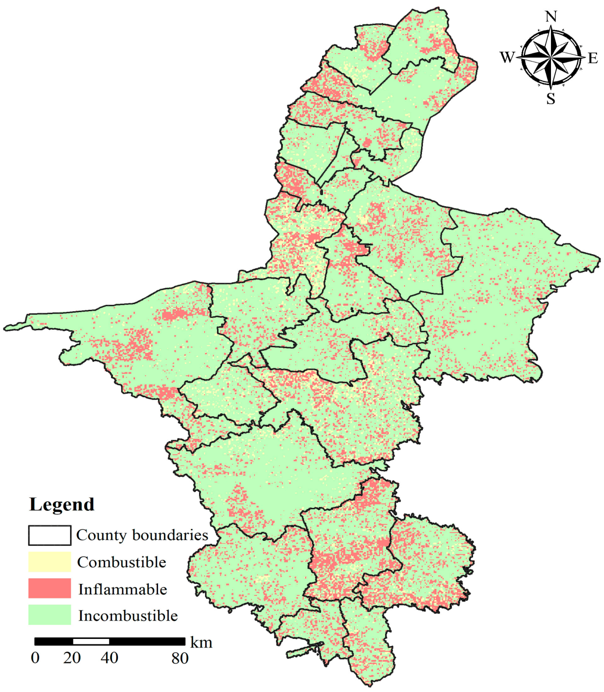


**Figure 4.** Combustible load distribution (the combustible load refers to the combustible load in forested areas, measured in units of tons (t)).

### 2.2.4. Socioeconomic Data

The population grid data (30 arcsec), building grid data (30 arcsec), and GDP data (30 arcsec) were sourced from the Census Office of the Ningxia Hui Autonomous Region. As illustrated in Figure 5, regions characterized by high population density, robust economic activity, expansive building coverage, and a substantial number of buildings exhibit a notable concentration in the Jinfeng District, Xingqing District, Xixia District, Shapotou District, and Yuanzhou District.

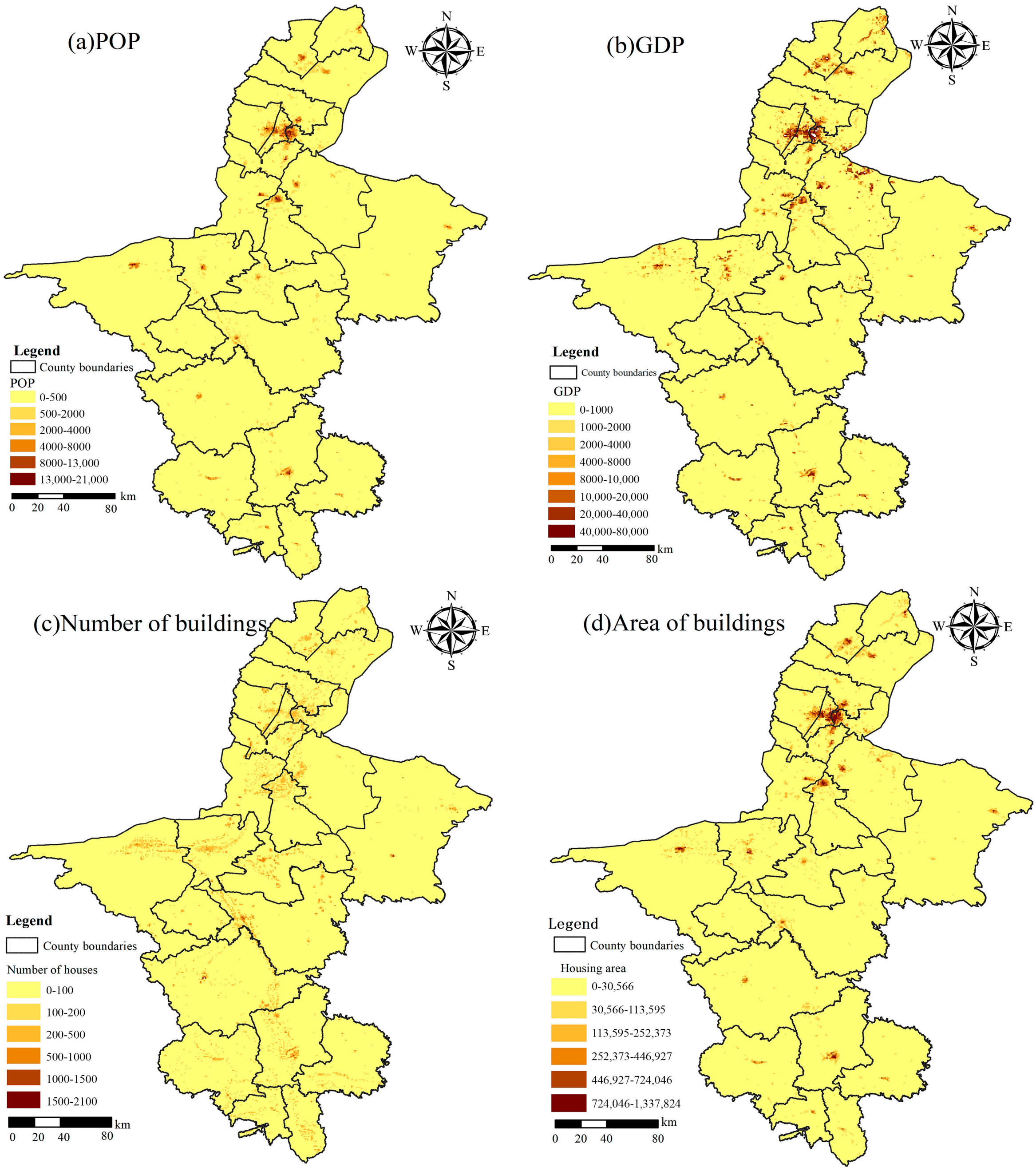


**Figure 5.** Map of socioeconomic conditions in Ningxia Autonomous Region (the POP is measured in "individuals", the GDP is quantified in "thousands of yuan", the count of buildings is in "units", and the building area is assessed in "square meters").

While wildfires typically occur in forested areas, human activities can play a crucial role in their propagation and impact. The quantity of buildings, building density, and the condition of infrastructure can significantly affect the speed and extent of fire spread. Therefore, we consider the introduction of the building area variable to be highly meaningful, as it takes into account the potential impact of these human factors on wildfires. Our study aims to provide a comprehensive approach that considers various factors, encompassing both natural and human elements, to more accurately predict wildfire occurrence risk. By introducing building area as a variable, our goal is to construct a more comprehensive model that better understands and forecasts wildfire events. Through such comprehensive analysis, we not only improve the integrity and accuracy of the forest fire risk prediction model, making it a solid guarantee for forest fire risk management, but also expect to minimize the risks faced by humans in the Wildland–Urban Interface (WUI) region. We believe that this comprehensive analysis method will provide a powerful tool for achieving these goals.

### *2.3. Research Methodology*

Figure 6 illustrates the technical workflow of our study, meticulously designed to establish a robust framework for generating predictive and forecasting maps regarding forest fire occurrences in the Ningxia region. The initial phase involves a comprehensive investigation to identify the pivotal driving factors significantly influencing the occurrence of forest fires in Ningxia. These identified factors subsequently serve as indispensable input data for our forest fire prediction model.

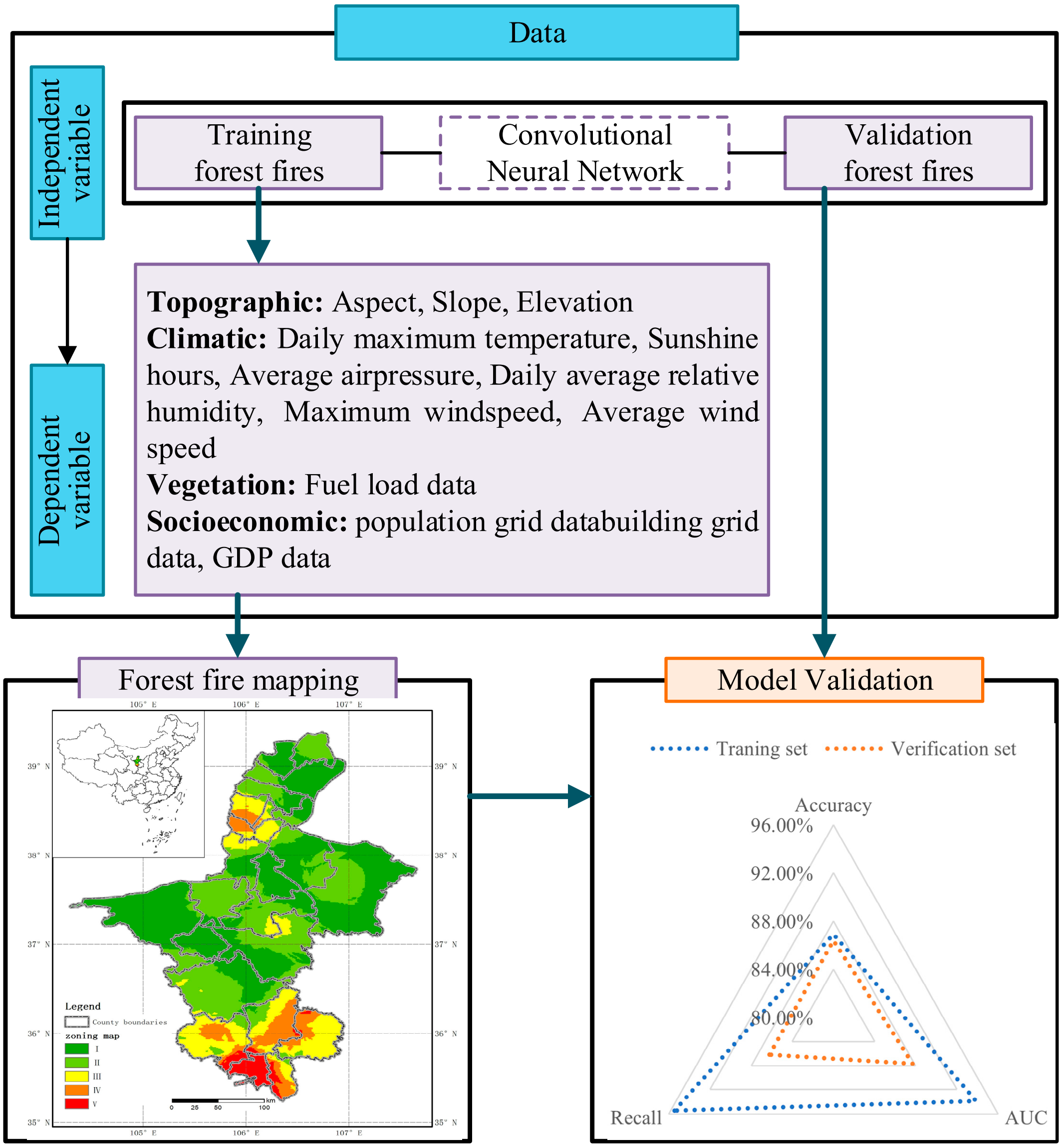


**Figure 6.** Technical flow chart.

Our model of choice is a sophisticated deep learning Convolutional Neural Network (CNN). In our approach, we allocate seventy percent of the available samples for model training, while the remaining thirty percent is reserved for validation purposes. To assess the model's performance, we employ a rigorously selected set of well-established evaluation metrics. The entire modeling process is executed within a Python 3.8 environment. Our objective is to forecast the occurrence of forest fires in the Ningxia region, create spatial probability maps, and classify fire occurrences.

### *2.4. Convolutional Neural Network (CNN)*

Convolutional Neural Network (CNN) models are one of the most important classical structures in deep learning models [28]. Convolutions applied within a multi-layer feed-forward neural network framework exhibit a network architecture distinguished by employing distinct sets of convolutional kernels in every layer. These kernels serve to extract valuable features from data points with localized significance [29]. CNN kernels represent different receptors that can respond to various features; the activation function simulates the function that only neuroelectric signals above a certain threshold can be transmitted to the next neuron [30]. The process of convolution significantly diminishes the learning intricacy of the network model, resulting in fewer network connections and weight parameters. This attribute simplifies the training process compared to an equivalently sized, fully connected network [31]. A Convolutional Neural Network (CNN) that incorporates local connectivity, weight sharing, downsampling, and dimensionality reduction [30].

As shown in Figure 7 and Appendix A, an 8-layer convolutional neural network was created, consisting of a sequence of Convolutional Layers (Conv layers), Batch Normalization (BN layers), and utilizing the LeakyReLU activation function. This CNN architecture was meticulously designed to cater to the specific requirements of the forest fire occurrence prediction task. The dataset was partitioned into a 7:3 ratio for training and validation purposes. The network's parameters were extensively configured, including a learning rate set at 0.001, a weight decay of 0.01, a momentum value of 0.9, and a fixed L1 regularization factor of 0.01, and parameter optimization was carried out using the stochastic gradient descent (SGD) optimization algorithm. These parameters and the CNN structure, which includes the number of layers, parameter settings, and execution standards for the convolutional layers, were thoughtfully crafted to optimize the model's performance in the context of forest fire occurrence prediction [32].

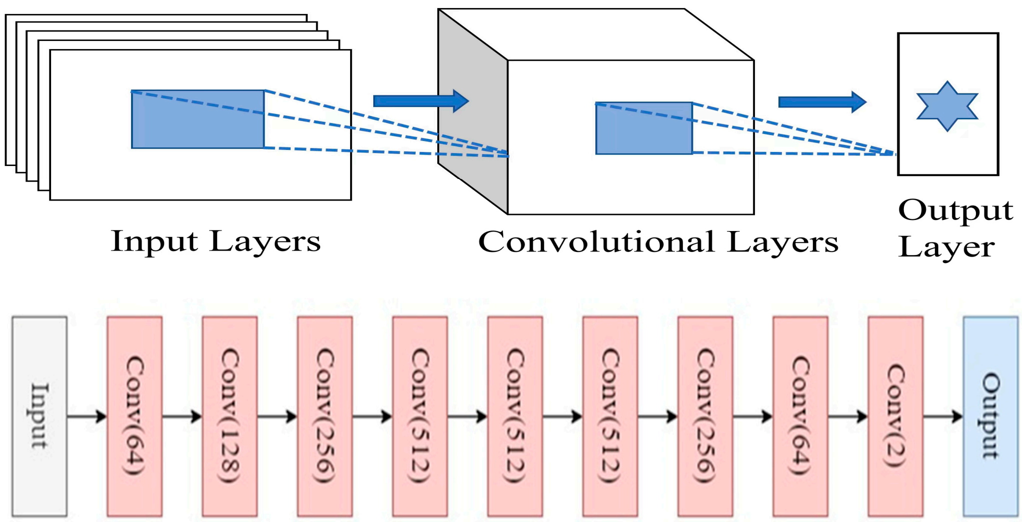


**Figure 7.** Network Structure Diagram.

To comprehensively evaluate the performance of our forest fire occurrence prediction model, we used a variety of evaluation metrics, including AUC (Area Under the Curve), Recall, and Accuracy. These metrics can reveal the predictive power of the model from different perspectives, helping us to more fully understand the model's performance.

AUC (area under the curve): AUC is a measure of the classification performance of a model, which reflects the cumulative difference in the prediction probabilities of positive and negative samples by the model. The value of AUC ranges between 0 and 1, with a higher value indicating better classification performance of the model.

Recall rate: The recall rate, also known as the recall, is an indicator that measures the ability of a model to find all positive samples. In the context of forest fire prediction, a high recall rate means that the model can accurately predict more fire events and reduce the possibility of false negatives.

Accuracy: The accuracy is an indicator of the ability of a model to correctly predict samples. In forest fire prediction models, a high accuracy rate indicates that the model can accurately predict whether a forest fire will occur. Through comprehensive analysis of these evaluation metrics, we can see that our forest fire occurrence prediction model performs well in terms of classification performance, recall, and accuracy. This provides a strong scientific basis for us to develop more effective forest fire prevention and response measures in the future.

$$AUC = \int_0^1 TPR(f)df, \tag{1}$$

$$Recall = \frac{TP}{TP + FN}, \tag{2}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{3}$$

$TPR(f)$ represents the true positive rate at a given false positive rate $f$; $TP$ and $TN$ represent the true positives and true negatives, respectively, while $FP$ represents the false positives (negative samples that are misidentified) and $FN$ represents the false negatives.

## 3. Results

### *3.1. Model Validation*

As depicted in Figure 8, our findings indicate strong performance and efficacy for the method outlined in this paper. Specifically, the training set achieved an Accuracy of 86.9%, Recall of 95.5%, and AUC of 93.9%, while the test set yielded an Accuracy of 84.3%, Recall of 86.2%, and AUC of 87.7%, respectively, showing the good performance and effectiveness of the method constructed in this paper. The significance of these results is that our approach demonstrates relatively high levels of accuracy, recall, and AUC on both the training and test datasets. This indicates that our model can effectively identify and predict the risk of forest fires. High accuracy signifies the model's ability to correctly classify fire events, high recall suggests that the model can capture most of the actual fire events, and a high AUC indicates that the model performs well under different threshold values. This is of paramount importance for forest fire prevention and early warning, as it assists relevant authorities in optimizing resource allocation and implementing control measures. The reasons behind these results lie in our utilization of deep learning CNN technology in conjunction with multiple data sources, enabling us to more accurately capture the complex patterns of fire occurrence. Furthermore, our approach takes into account various factors such as combustibles, GDP, POP, meteorology, and buildings to enhance the model's predictive performance.

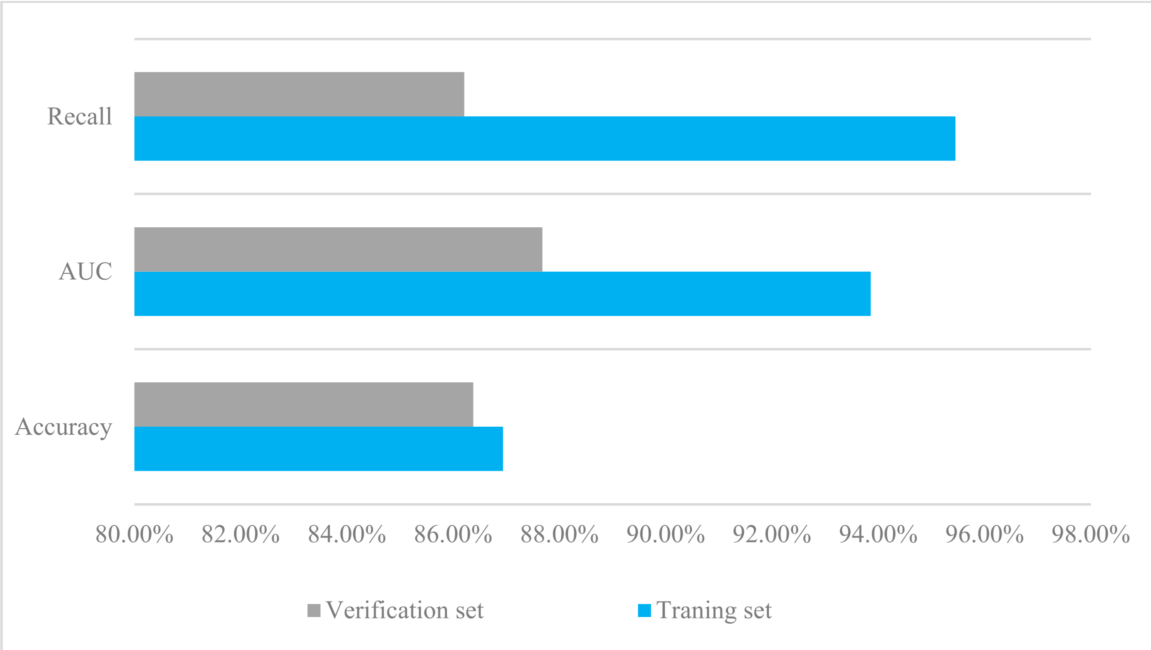


**Figure 8.** The evaluation accuracy of the Convolutional Neural Network model (blue and green represent the training set and validation set, respectively).

By comparing our findings with previous research [6,7], we can demonstrate the outstanding performance of our method in the field of forest fire prediction and how it addresses the limitations of previous studies.

*3.2. Fire Risk Probability and Zoning*

As shown in Figure 9 and Table 4, our results indicate that in Ningxia Hui Autonomous Region, the high-probability and high-incidence areas of forest fires are located in Longde County and Jinyuan County, accounting for 3.30%, while the higher probability and higher incidence areas are located in Pengyang County, Xiji County, Yuanzhou District, Tongxin County, and Xixia District of Yinchuan City, accounting for 7.04%. The rest of the areas belong to low or lower-incidence areas. Due to the limited forest land assets, sparse population distribution, and relatively lagging economic development in the Ningxia Autonomous Region, the prediction results of forest fires are highly consistent with survey data. The forest fire risk probability and zoning map show that the probability ranges of 0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, and 0.8–1 correspond to five levels of I, II, III, IV, and V, respectively, with the meanings of "essentially no fire", "not prone to fire", "possibly occurring", "likely to occur", and "very likely to occur". The predicted results of forest fire occurrence are in very high agreement with the survey data due to the limited presence of woodland assets, along with sparse population distribution and economic underdevelopment within the Ningxia Autonomous Region [33]. Therefore, the overall occurrence of forest fires is low compared to the whole country [8]. Meanwhile, the areas of Lunde and Jingyuan Counties, Panyang County, Xiji County, Yuanzhou District, Concentric County, and Xixia District of Yinchuan City have high population and economic geographic concentrations [34]. In Lunde County, forest cover stands at 37.43%, while Jinyuan County boasts a higher rate of 42.24%. These areas, with their significant forest coverage, provide ample fuel for wildfires or wildland fires, making them high-risk zones in the entire autonomous region. Analysis of fire data reveals that over 80% of these fires are human caused, underscoring the profound influence of human activities in these regions. In Ningxia, the majority of forest fires are attributed to man-made causes, with ritual fires being a predominant factor. Consequently, it is imperative to enhance the management of potential ignition sources to curb the incidence of fires at their origin. This strategy should be complemented by efforts to boost public awareness and education, focusing on instilling a comprehensive understanding of fire prevention among residents. Expanding research to include real-time monitoring in areas with a high frequency of fires is also vital. Implementing targeted measures in these high-occurrence zones, such as effective vegetation management and stringent control of fire sources, is essential for mitigating the risk and impact of wildfires.

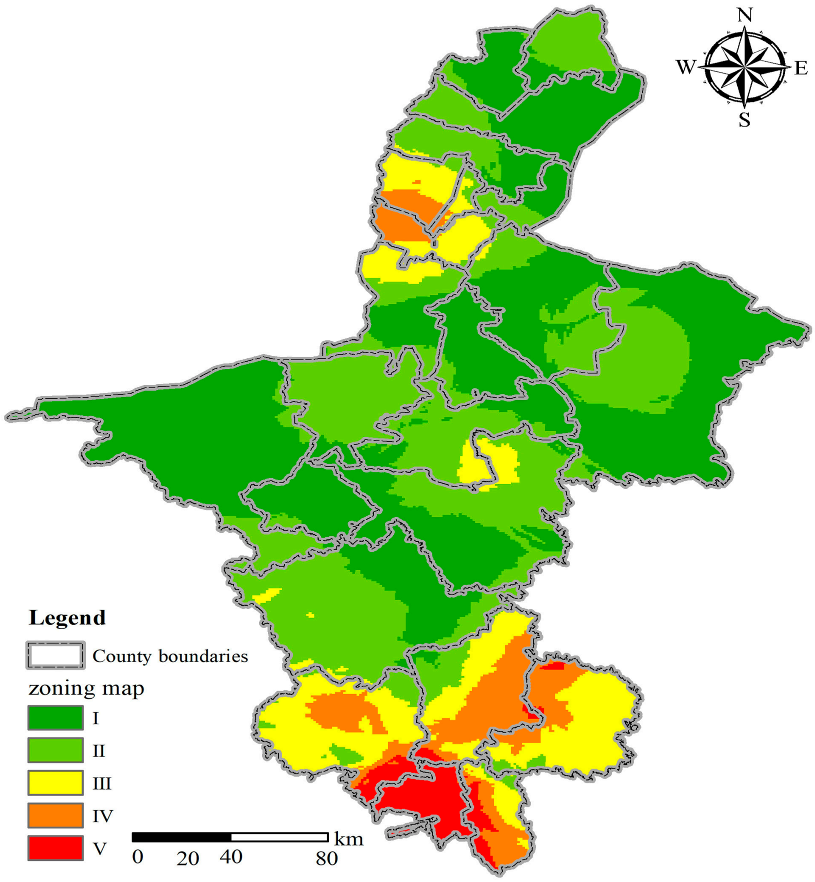


**Figure 9.** Probability and zoning map of forest fire risk in Ningxia Hui Autonomous Region (for probability and division classification, reference Table 4).

**Table 4.** Forest fire zones [8] in Ningxia Hui Autonomous Region.

| Probability Classification | Risk Zoning | Grade | Description | Percentage |
|---|---|---|---|---|
| 0–0.2 | I | very low | unlikely | 42.46% |
| 0.2–0.4 | II | low | low possibility | 33.54% |
| 0.4–0.6 | III | middle | might happen | 13.66% |
| 0.6–0.8 | IV | high | could happen | 7.04% |
| 0.8–1 | V | very high | vigilance is required | 3.30% |

## 4. Discussion and Conclusions

### *4.1. Discussion*

By leveraging the integrated use of deep learning Convolutional Neural Networks (CNNs) technology and multi-source data, our research has successfully constructed a highly accurate and practical wildfire occurrence prediction framework. This framework can provide robust support for wildfire prevention and control at the interface between forests and urban areas. This discovery is closely tied to the research on the wildfire issue at the forest–urban interface because our approach not only enhances prediction accuracy but also strengthens our understanding of potential occurrences. This finding is closely related to research on wildfires at the forest–urban interface because our method not only improves prediction accuracy but also enhances our understanding of potential occurrences.

To ensure effective forest fire management and prevention in different areas, it is essential to optimize resource allocation and implement tailored measures according to the specific fire occurrence zone conditions [8]. This involves a focused approach to safeguarding the ecological security of critical regions and developing zoning management strategies in a scientifically informed manner. It also calls for the concentration of prevention and control efforts and improvements in the forest fire monitoring system [35].

Continuous efforts are needed to enhance infrastructure development, particularly through the establishment of a forest fire video monitoring system. This system should leverage advanced technologies such as infrared detection, high-definition visible-light video, and intelligent smoke and fire identification to strengthen early warning capabilities in high-occurrence areas and other key locations [36,37]. Additionally, it is recommended to implement reasonable measures such as cutting, pruning, and de-irrigation for units with high occurrence levels of fire. These actions aim to reduce the occurrence risk and improve fire source management, ultimately minimizing fire damage [38]. The management of forest fire sources should be a priority, with a specific focus on controlling human-made fire sources. Historical data has shown that human-made fire sources are the primary cause of forest fires in the Ningxia Hui Autonomous Region. In areas with a high occurrence risk of forest fires, there is a need for intensified public education on forest fire safety, coupled with stringent control of potential sources of forest fires in key areas [32].

This study enhances the scope of forest fire management by emphasizing the strengthening of forest firefighting teams and improving infrastructure for fire prevention teams. This approach complements our analytical focus, which, unlike most previous studies [39–41] that centered on predicting forest fire occurrences using meteorological, topographical, economic, and social factors within distinct administrative units like counties and cities, adopts a more integrated methodology. Drawing parallels with earlier research utilizing similar modeling techniques, particularly those employing machine learning methods, our study aligns with approaches like the Maxent (maximum entropy model) used in predicting spatial patterns of forest fires. Maxent, a widely recognized tool in ecological modeling for species distribution, has shown efficacy in identifying potential high-risk areas based on various environmental variables. Similarly, our study leverages deep learning Convolutional Neural Networks (CNNs) to integrate diverse data sources, providing a more holistic view of potential fire risks that transcend administrative boundaries. This methodological alignment demonstrates the growing importance of advanced machine learning techniques in enhancing the accuracy and comprehensiveness of forest fire risk assessments.

Our research represents a departure from the traditional reliance on administrative districts as evaluation units, thereby expanding the applicability of GIS grid methodologies. However, it is not without its limitations, which present opportunities for further advancements. Firstly, future studies can be enhanced by incorporating a larger survey data sample size, thereby improving the predictive accuracy of the model. Secondly, our future research aims to refine the predictive model by narrowing the focus to a smaller study area and integrating high-resolution satellite imagery, UAV aerial photography, and ground survey data in regions prone to wildfires. This refined approach holds promise to yield even more accurate insights into vegetation moisture content, soil moisture, and localized meteorological monitoring, facilitating real-time predictions and early warnings in high-risk zones.

In addition, our study underscores the significance of combining applied modeling techniques with geospatial tools in establishing priority zones (risk zones) for management actions within the research area. Through this methodology, we are able to pinpoint high-risk areas more precisely and provide more specific recommendations to management departments for targeted intervention strategies. This not only aids in the more efficient allocation of resources but also greatly reduces potential losses due to forest fires or other natural disasters. Consequently, our research offers a valuable reference for the integration of modeling techniques with geospatial tools in disaster risk management and mitigation efforts. In summary, the significance of this study lies in its departure from traditional evaluation units based on administrative districts, broadening the application of GIS grid methodologies, and providing directions for future improvements. Concurrently, by merging modeling technologies with geospatial tools, we empower management departments with more accurate and detailed information and advice for effective strategy formulation, thereby mitigating risks posed by natural disasters.

### *4.2. Conclusions*

In this research, we embarked on a comprehensive examination of wildfire occurrences within the Ningxia Hui Autonomous Region. Our approach was multifaceted, incorporating diverse data sources such as combustibles, GDP, population demographics, meteorological data, building density, and grid data. These elements were adeptly integrated using deep learning Convolutional Neural Networks (CNNs) to effectively predict potential fire risks. The synergy of grid data and CNN technology in our framework culminated in the development of an exceptionally accurate and practical model for forecasting forest fire occurrences at a provincial level. Our analysis specifically pinpointed Lunde County and Jinyuan County as high-risk areas for wildfires. The findings from this study offer invaluable insights for the development of forest fire prevention strategies, forecasting, and the implementation of science-driven zoning management practices.

To conclude, our research underscores the vital importance of proactive forest fire management and the utilization of advanced technologies in this field. It further stresses the significance of enhancing public awareness and executing region-specific strategies in areas frequently affected by wildfires. By bridging the identified research gaps, we anticipate a notable advancement in the efficacy of forest fire prevention and control measures in future endeavors.

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**Data Availability Statement:** The data used in this study were obtained from the Ningxia fire risk survey. In accordance with data confidentiality policies, the data are currently not available for public access.

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## Appendix A

**Algorithm A1:** Convolutional Neural Network (CNN)

**Input**: Forest Fire Occurrence Driver Factors Data
**Output**: Trained Model, Occurrence Maps, and Fire Level Classification

```
  # Step 1: Define the CNN model
def create_cnn_model():
    model = Sequential()
    # Step 2: Define convolutional layers, Batch Normalization, and LeakyReLU activation
    model.add(Conv2D(64,(3,3), activation='leaky_relu', input_shape=(input_shape)))
    model.add(BatchNormalization())
    # Add more convolutional layers, Batch Normalization, and LeakyReLU activation as needed
    # Step 3: Define fully connected layers (if applicable)
    model.add(Flatten())
    model.add(Dense(128, activation='leaky_relu'))
    # Step 4: Define the output layer
    model.add(Dense(num_classes, activation='softmax')
    # Step 5: Compile the model
    model.compile(optimizer=SGD(learning_rate=0.001, momentum=0.9, decay=0.01),
                 loss='categorical_crossentropy', metrics=['accuracy'])
    return model
# Step 6: Create an instance of the CNN model
cnn_model = create_cnn_model()
# Step 7: Load and preprocess the dataset
X_train, y_train, X_validation, y_validation, X_test, y_test = load_and_preprocess_dataset()
# Step 8: Train the model
cnn_model.fit(X_train, y_train, validation_data=(X_validation, y_validation), epochs=10)
# Step 9: Evaluate the model's performance on the test set
test_loss, accuracy = cnn_model.evaluate(X_test, y_test)
# Step 10: Calculate Recall and AUC
recall = calculate_recall(X_test, y_test)
auc = calculate_auc(X_test, y_test)
# Step 11: Return the trained model, accuracy, recall, and AUC
return cnn_model, accuracy, recall, auc
```

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