CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Review of the Research Process

Throughout this project, I explored the use of machine learning to predict wildfire risk based on environmental data. After trying out four different models—XGBoost, Random Forest, Logistic Regression, and Support Vector Machine—I found that XGBoost gave the best results overall. It reached an accuracy of around 79.3%, with a precision of 89.4%, recall at 84.0%, and an F1-score of 86.6%. These numbers suggest that the model was quite effective at telling apart areas with and without fire risk.

Apart from just looking at performance scores, I also analyzed which features the model relied on most. Temperature, NDVI (which shows how healthy the vegetation is), and wind speed turned out to be the most important variables. These make intuitive sense because heat, dryness, and wind all play major roles in whether a fire is likely to happen.

Of course, the model wasn't perfect. It sometimes got things wrong—for example, predicting fire in places with low vegetation but high humidity, or missing fire in areas that were hot but still had healthy vegetation. These mistakes helped me understand where the model might need more work or better inputs.

Still, the overall results were promising. The model didn't just work well on the original training data—it also held up during cross-validation. With a 5-fold cross-validation mean accuracy of about 78%, and low standard deviation (±0.02), the results seem stable. XGBoost seemed to strike a better balance between precision and recall than the other models. This really matters in wildfire prediction, since too many false alarms or missing actual fires can both lead to serious problems.

Looking back, the results from this study suggest that machine learning has real potential in predicting wildfire risk. With the right inputs, models like XGBoost can actually give useful predictions that might help reduce the impact of fires.

5.2 Model Performance Metrics

When analyzing the results, I noticed that the XGBoost model worked the best out of the four I tested. Compared to Random Forest, Logistic Regression, and SVM, it gave more consistent and balanced predictions. The model reached around 79.3% accuracy, and its precision and recall were also quite high—89.4% and 84.0%, respectively. This made it feel like a solid choice for distinguishing between fire and no-fire situations. While the other models had their strengths too, XGBoost seemed to handle the data patterns more effectively overall.

The AUC score of 0.86 adds to the confidence that the model handled thresholds reasonably well. The five-fold cross-validation gave an average accuracy close to 78%, with only a small variance, suggesting that the model remained consistent even when trained on different parts of the data.

As for the inputs that mattered most, the model pointed to temperature, NDVI (vegetation index), wind speed, relative humidity, and road density. These results are quite reasonable—wildfires usually relate closely to dry conditions, vegetation stress, and how close the land is to infrastructure.

5.3 Strengths and Weaknesses of the Model

From a practical point of view, there are several things this model does well. It shows a strong ability to flag risk without triggering too many false alarms or missing real fire situations—something very important for actual emergency planning. It also doesn't require a huge amount of data to function reasonably well. Even with just 700 samples, it produced results that seem trustworthy.

Another helpful aspect is that it gives insight into which variables matter most. This makes it easier for local decision-makers to focus on the right things—like watching areas with high temperatures and low vegetation health. The model is also not a black box; people can still get a sense of how it arrives at a prediction, which is useful in real-world use where transparency can matter.

But, it's not perfect. The model still works only with structured, tabular data and doesn't take visual or geographic context into account directly. That might limit its sensitivity in some cases, like when spatial factors play a larger role. Also, because the data used is limited in time and scope, how well the model would generalize to very different areas or extreme conditions isn't fully clear.

5.4 Practical Implications

Despite those limitations, the results do offer useful ideas for how wildfire prediction tools could be applied. For example, this kind of model could be built into an alert system that uses live environmental data—temperature, NDVI, wind, humidity—to assess risk in near real time. This could help agencies prioritize areas for watch or even plan preventative actions.

Because the model gives a ranked list of feature importance, resources could be better allocated. Communities in drier, hotter zones with stressed vegetation could be targeted more for fuel reduction, education, or response drills. Since the model doesn't rely on massive datasets or deep learning infrastructure, it might be usable even in areas where resources are limited.

Also, the fact that its output is relatively easy to interpret means it could be paired with tools like GIS dashboards or mobile apps. That way, field teams could access the information quickly and act accordingly without needing technical expertise.

5.5 Limitations and Future Work

This project only scratches the surface when it comes to predicting wildfires. The dataset we used, while useful, was relatively limited in size and location. Working with more data from other regions or years could lead to different outcomes, and possibly stronger models overall.

It might also help to include other types of information. Some researchers have started using images from satellites or drones to spot signs of fire risk, and combining that with weather or vegetation data could improve the results. We didn't explore that in this study, but it seems like a logical next step.

Another idea is to look at how wildfire conditions change over time. Most of our data was static, like one-time measurements or averages. But in real life, fire risk doesn't stay the same. Changes in rainfall, wind, or even human activity could all play a role. A model that captures those trends might be more useful for early warnings.

There's also the question of how understandable these models are. Even when a model performs well, it's not always clear why it made a certain prediction. That can be a problem if the results are meant to be used by people in the field. Finding a way to make models both accurate and easier to explain could be something worth looking into.

5.6 Final Conclusion

Looking back on this project, I think it gave me a valuable chance to explore how machine learning can be applied to a real-world problem like wildfire risk. I tried several models—XGBoost, Random Forest, Logistic Regression, and SVM—and after some comparisons, XGBoost gave the most reliable results. Its predictions were fairly accurate, and it seemed good at picking out which areas might be more at risk. Of course, it's not perfect, but it did give a sense that machine learning could be a useful tool in fire prevention if used properly.

What surprised me a bit was how much the different features affected the outcome. Things like temperature, wind speed, and NDVI clearly had a big influence on how the model behaved. It made me realize that even small changes in environmental conditions can shift the results. I guess it helped me see wildfires as not just random events, but something that can be studied and maybe even predicted with the right tools.

That being said, I also noticed that building models isn't always straightforward. Some parts were frustrating—like when the model misjudged cases that seemed obvious, or when it got too focused on certain patterns and ignored others. But I also learned that this is pretty normal in data science. By trying things like feature selection and cross-validation, I gradually found better ways to deal with those problems.

Overall, this project wasn't just about getting a good accuracy score. It was also about learning how to work with messy data, how to question the results, and how to explain what a model is doing. I still have a lot to learn, but I feel like I've taken a good step in understanding how data science connects with real-life issues. And honestly, it made me more curious to dig deeper into these kinds of problems in the future.