AI expands high-quality urban flash flood forecasts globally

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Abstract

Flash floods account for approximately 85% of flooding cases worldwide and exhibit the highest mortality rates among hydrological hazards. Yet, effective early warning systems remain largely absent in the Global South due to a lack of dense observational networks. In this study, we present an AI-based global urban flash flood prediction system that generalizes effectively across unseen regions. Our approach leverages recent advances in deep learning, which allow for a paradigm shift: For the first time, we can directly train models on global ground truth data extracted from millions of news articles, as opposed to scarce and expensive measures of physical quantities. We demonstrate that this deep learning approach achieves results comparable to the state-of-the-art National Weather Service Flood and Flash Flood Warnings in the United States, despite using lower-quality inputs that are available globally. The system is operational and provides free and open real-time forecasts in over 150 countries (`https://g.co/floodhub`)—a significant step toward democratizing access to high-quality disaster warnings and building global socioeconomic resilience in the face of an accelerating hydrological cycle.

1 Introduction

Floods represent a ubiquitous and escalating threat to human populations and global economies, driving massive annual losses in life and property through widespread damage to infrastructure and agricultural systems. Among hydrological hazards, flash floods, characterized by rapid onset, intense flow velocity, and highly localized impact, pose a disproportionate and particularly challenging risk, often striking vulnerable communities with minimal lead time for effective response [1,2]. According to the World Meteorological Organization (WMO), flash floods account for approximately 85% of the flooding cases worldwide and have the highest mortality rate, with more than 5000 lives lost annually, making them one of the world's deadliest disasters [3].

Early warning systems (EWS) have proven to save lives and mitigate damage from natural disasters. Countries with less comprehensive Multi-Hazard Early Warning Systems face a disaster-related mortality ratio nearly six times higher than those with substantial to comprehensive coverage [4]. Schröter et al. estimated that a 12-hour flash flood warning lead time can provide a 60% reduction in damages [5].

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A stark geographical dichotomy, however, defines the global capacity to mitigate the threat from floods and especially flash floods. In developed nations, robust EWS provide actionable, high-resolution forecasts that have proven to greatly reduce mortality [6]. In contrast, such infrastructure remains largely absent across vast, vulnerable regions of the Global South: The WMO found that less than half of the Least Developed Countries and only one third of Small Island Developing States have access to multi-hazard EWS [4]. This “warning gap” creates unequal outcomes: while Asia experienced 40% of all flood events between 2000 and 2019, it accounted for more than 90% of people affected by floods worldwide [2].

Regions with advanced meteorological and hydrological infrastructure predict flash floods through guidance systems such as the United States Flash Flood Guidance (FFG) [7, 8] and the European Runoff Index based on Climatology (ERIC) [9]. FFG calculates dynamic rainfall thresholds for the specific intensity of precipitation required over a short duration to exceed the soil’s infiltration capacity and initiate surface runoff on small streams. Operationally, a warning is triggered if the quantitative precipitation forecast for a given period—typically one, three, or six hours—exceeds the predetermined FFG threshold for that basin. Focusing on riverine flash floods, ERIC simulates the current soil moisture and runoff using the LISFLOOD hydrological model [10] and compares the forecasted runoff against a long-term climatological database. Operationally, a warning is triggered if the forecast exceeds a statistical threshold, such as the 5- or 20-year return period.

The efficacy of these approaches relies on the availability of high-resolution, low-latency observational data—such as ground-based radar—and homogeneous, high-quality historical meteorological records to establish accurate baselines. Unfortunately, vast regions of the Global South lack such data and, so far, global forecasting initiatives have struggled to compensate for the missing observations. Systems like the WMO’s Flash Flood Guidance System (FFGS) [11], which relies on the FFG approach, provide a robust framework for national meteorological services, but they remain constrained by the quality of input data and the need for local calibration against historical events that may not be instrumentally recorded. Addressing the warning gap therefore requires a fundamental change: moving away from calibration against sparse physical sensors and toward a system that can learn from a new class of global ground truth data. Artificial Intelligence (AI) advances have enabled this paradigm shift: we can now train generalizable, global models that do not need local calibration, and we can use AI to collect and curate global ground truth datasets from existing textual descriptions.

In this paper, we present an AI-based global urban flash flood prediction system that generalizes effectively even in regions with sparse data. We trained and evaluated the system on *Groundsource* [12], a ground truth dataset that the Large Language Model (LLM) Gemini [13] extracted from news articles. Further, we evaluate the extent to which this deep learning approach can improve global access to flash flood forecasts. Our approach achieves performance comparable to state-of-the-art National Weather Service (NWS) Flood and Flash Flood Warnings in the U.S., even though it uses only globally available lower-quality inputs. On the basis of the model and extensive experimental validation described herein, we developed an operational system that produces short-term (24-hour) flood forecasts, currently available in over 150 countries. These forecasts are available in real time without barriers to access, such as monetary charge or website registration (`https://g.co/floodhub`).

2 Methods

Our flash flood forecasting system uses a Long Short-Term Memory network (LSTM) [14], an architecture that has proven well-suited for environmental and specifically hydrological time-series data [15, 16]. Specifically, we build upon the work by Nearing et al., who developed a hydrological forecast model for riverine floods using LSTMs [17]. As flash floods are mostly driven by local precipitation—in contrast to riverine floods, which are driven by water contribution from upstream basin areas—our model does not operate at a basin scale. Instead, we feed the model with input data as pixels with a spatial resolution of $0.2^\circ \times 0.2^\circ$, with study regions restricted to land masses.[1] The spatial resolution is primarily driven by the granularity of globally available atmospheric data.

The model integrates static geophysical properties with dynamic hourly meteorological data, detailed below. Specifically, it processes a 7-day hourly historical hindcast sequence followed by a 24-hour hourly forecast window. The model generates a score that represents the probability of a flash flood event occurring within the subsequent 24 hours in the target region.

The architecture processes static attributes through a series of dense embedding layers to produce a fixed-length representation. Dynamic features are organized into discrete feature groups, by their provider, each of which is independently embedded to capture group-specific temporal dynamics. We handle missing data in the input streams with the masked mean architecture described in Gauch et al. [18]: a mechanism that discards missing data and calculates a mean across the embedded feature groups to aggregate information from valid observations. This temporal summary is concatenated with the embedded static attributes—which are repeated across the sequence length—and fed into the LSTM. Finally, a series of two fully connected layers with a sigmoid output activation function yields an uncalibrated probabilistic score. Figure 2 illustrates the model architecture, and Appendix A describes the architectural hyperparameters in more detail.

The training objective was a binary cross-entropy loss between the predicted probability and the observed flood labels from Groundsource [12]. Groundsource is a collection of millions of localities (streets, towns, districts, countries, etc.) and dates that have experienced floods, extracted from publicly available news articles using an LLM. We focus on areas with a population density exceeding 100 people per km^2. This ensures sufficient media coverage to provide training and evaluation data, while prioritizing human impact: the covered area accounts for approximately 88% of the world's population, based on WorldPop data [19]. Figure 1 shows a map of the resulting spatial coverage. The model's output is a score representing the likelihood of a news-worthy flood occurring in the study region during the following 24 hours. As the labels are highly skewed towards negatives, we up-sampled positive samples to constitute 20% of the training data. Hence, the resulting model is uncalibrated and the output cannot directly be interpreted as a probability for a flood to occur.

Input data

We use embeddings from AlphaEarth Foundations [20] as static attributes that let the model adapt its timeseries processing to the characteristics of each individual region. AlphaEarth is a geospatial foundation model that generates 64-dimensional, 10-meter resolution embeddings from multimodal Earth observation data, including optical, radar, and climate sources. We extract the embeddings from 2020 and spatially average their values for each prediction area.

Our meteorological forcings come from the following providers:

- Single-level forecasts from the ECMWF Integrated Forecast System (IFS) High Resolution (HRES) atmospheric model. The variables we use are: total precipitation (TP), 2m temperature (T2M), surface net solar radiation (SSR), surface net thermal radiation (STR), snowfall (SF), and surface pressure (SP).
- Single-level precipitation forecasts from GraphCast [21], a machine learning-based global weather forecasting system that predicts meteorological variables at a 0.25° resolution.
- Precipitation estimates from the National Oceanic and Atmospheric Administration

[1] Cutting off non-landmass area can cause irregular shapes, but for the sake of simplicity, we will nevertheless call the prediction areas "pixels" in this manuscript.

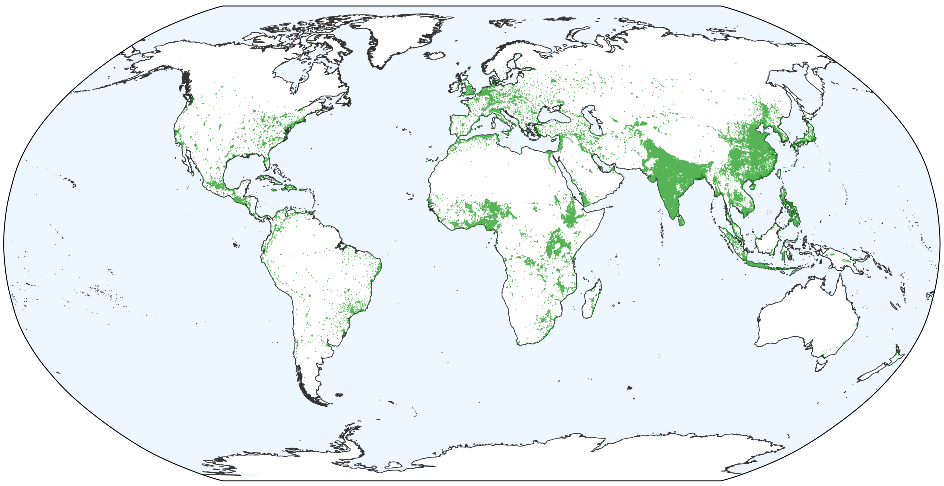

Figure 1: World map with the areas that our flash floods model is trained to predict highlighted in green. These correspond to areas with population density above 100 people per km^2, which cover approximately 88% of the world's population (source: WorldPop). Note that the operational system excludes some of the highlighted areas due to legal restrictions.

(NOAA) Climate Prediction Center (CPC) Global Unified Gauge-Based Analysis of Daily Precipitation.

- Precipitation estimates from the NASA Integrated Multi-satellite Retrievals for GPM (IMERG) early run.

All input data are area-weighted averages over the study regions, which are $0.2° \times 0.2°$ squares that are cropped to a low-resolution map of the landmasses. Similarly, we calculate the maximum precipitation value of the providers CPC, IMERG, and GraphCast in each study region for each hour.

Target and evaluation data

Ground-truth targets for flood events stem from the Groundsource dataset, a global repository of historical flood events extracted from over 5 million news articles. Groundsource utilizes natural language processing to structure unstructured textual reports into precise spatial polygons and temporal intervals at a daily resolution. As additional processing, we limit the duration of flood events to 3 days, and define events without end date to last one day.

Notably, Groundsource includes data for any kind of flooding, not just flash floods. Because we feed our model only with local meteorological information, we expect the system to mostly predict flash floods, but technically, the current system is trained and evaluated on any kind of flood. We see this as both a limitation and a feature at the same time—a limitation, because the distinction of flood type is lost, but a feature, because the framing as a classification problem allows for unified handling of arbitrary floods. We expect that future Groundsource versions will distinguish flood types, which would allow us to pass this distinction to the downstream flash flood prediction model.

Our training and evaluation data ranges from 2018 to 2025, which covers around 78% of the events in Groundsource. We chose this cutoff, as the dataset's recency bias would likely lead to larger gaps and geographical biases for earlier periods. Given this period, we trained and evaluated the model in a k-fold temporal cross-validation setting. The years 2018–2021 are always in the training set, while each of the subsequent years represents the evaluation split in one of the folds. In total, we can therefore evaluate on four years of data (2022–2025).

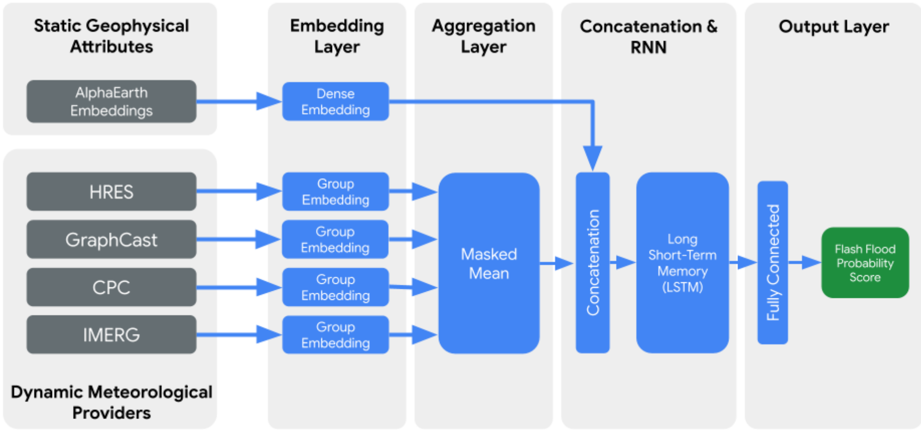

Figure 2: The architecture of the model used operationally to provide flash flood predictions on Google Flood Hub (`https://g.co/floodhub`).

Metrics

To evaluate whether AI-driven forecasting can reach operational standards, we benchmarked our system in the United States against the NWS Flood and Flash Flood warnings—a premier local expert system that uses dense sensor networks and high-resolution radar. We downloaded the NWS warnings from the Iowa Environmental Mesonet website [22]. For a consistent comparison, we aggregated NWS alert data to match the model's $0.2° \times 0.2°$ grid and 24-hour forecast window. This comparison involves distinct operational nuances: while our model generates forecasts at fixed daily intervals, the NWS issues warnings dynamically as meteorological threats evolve, occasionally issuing alerts after the recorded onset of flooding. Furthermore, although our spatial aggregation may not fully capture the spatial detail of the NWS, it provides a necessary baseline for global scalability.

Following the framing of flash flood prediction as a classification problem, we evaluate our system and the NWS warnings by means of precision and recall. Unfortunately, news reports of flood events only give a fuzzy picture of the events' spatial extents. Typically, the extracted extent in Groundsource will be larger than the actual area that was affected by flooding, as flooding generally does not follow the geopolitical boundaries that are used in textual descriptions. To account for these uncertainties, we define precision and recall as follows:

Precision We define a positive prediction at a modeled pixel as a true positive if an event that happened within the same time frame intersects the pixel's geometry in a non-negligible way. We define an intersection as non-negligible if the intersection of the pixel and the event geometries comprises at least 40% of the event area or of the pixel area. In other words, if the intersection is small relative to both the predicted area and the event, we do not count it as a hit. Conversely, we consider a prediction that does not intersect with an event as a false positive. Intuitively, this results in precision as a measure of the percentage of alerted areas that can be corroborated by an event in the ground truth.

Recall We consider an event as recalled if a pixel that has a non-negligible intersection with the event (as defined above) issued a warning at the beginning of the day during which the event started. Further, in line with the recall definition in the Groundsource paper [12], we use events from the Global Disaster Awareness and Coordination System (GDACS) [23] as the ground truth for this analysis. Because GDACS focuses on significant events, evaluating recall on this source of ground truth lets us ascertain that our model correctly alerts on impactful floods. To avoid meaningless polygons, we only consider GDACS events up to a size of 50,000 km^2.

3 Results and discussion

As the deep learning model outputs probability scores, we can sweep the classification threshold and therefore decide on the tradeoff between precision and recall (Figure 3a). Depending on the choice along this spectrum, we can achieve precision and recall values close to those of the NWS warnings, which are restricted to the U.S. It is important to note that all of the reported precision metrics are likely underestimates, as some real-world floods go unreported in the media, or are mislabeled by the LLM system in Groundsource, which incorrectly flags valid alerts as false positives.

Figure 3b shows the full precision–recall curve for the entire world. While there are more events globally, and the curve is therefore smoother, the overall shape indicates a global performance on par with the U.S.-based evaluation. This is expected, as all inputs to the model are globally available, and therefore high-resource countries like the U.S. have no particular advantage beyond potential better news coverage and improved grounding of the global forcings.

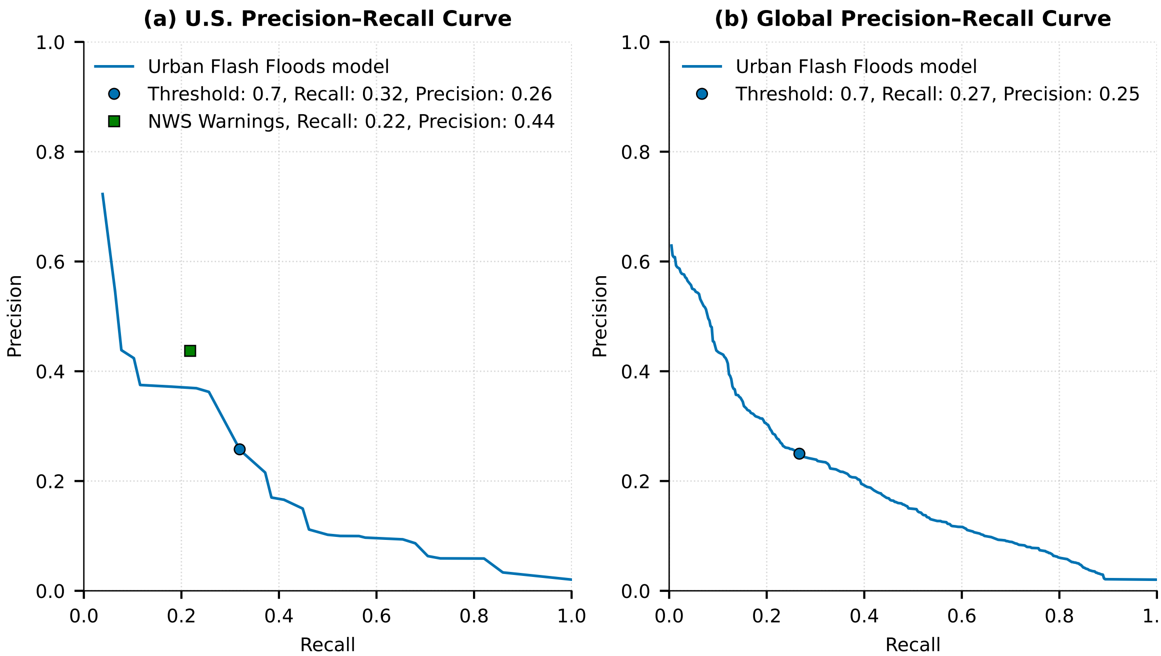

Figure 3: Precision–recall curve for the flash flood forecasting model (blue) evaluated in the U.S. (left) and globally (right). In the U.S., we can compare to the baseline of aggregated NWS Flood and Flash Flood Warnings (green square). The blue dot represents the results at a classification threshold of 0.7, which we use for the subsequent breakdown of per-country quality.

To provide further detail, Figure 4 breaks down the precision and recall performance by country at a classification threshold of 0.7. Inherently, the results for some countries in this analysis are subject to greater uncertainty than others, because the amount of ground truth events in Groundsource (used to calculate precision) and GDACS (used to calculate recall) varies as indicated in the bottom row of Figure 4. We excluded countries with less than 10 ground truth events from this analysis to limit the resulting noise. The precision values are homogeneous across most countries. Central Africa and parts of the Middle East/Asia have lower precision, which we largely attribute to the limited representation of these regions in Groundsource. This lack in coverage causes us to underestimate precision, as positive predictions are treated as false positives. In terms of recall, parts of South America and South-East Asia stand out with particularly high values. While we cannot exclude confounders such as the quality of GDACS events, we hypothesize that this might be due to their exposure to tropical storms. These extreme events are relatively easy to predict and well-covered in the Groundsource training data, resulting in more accurate warnings.

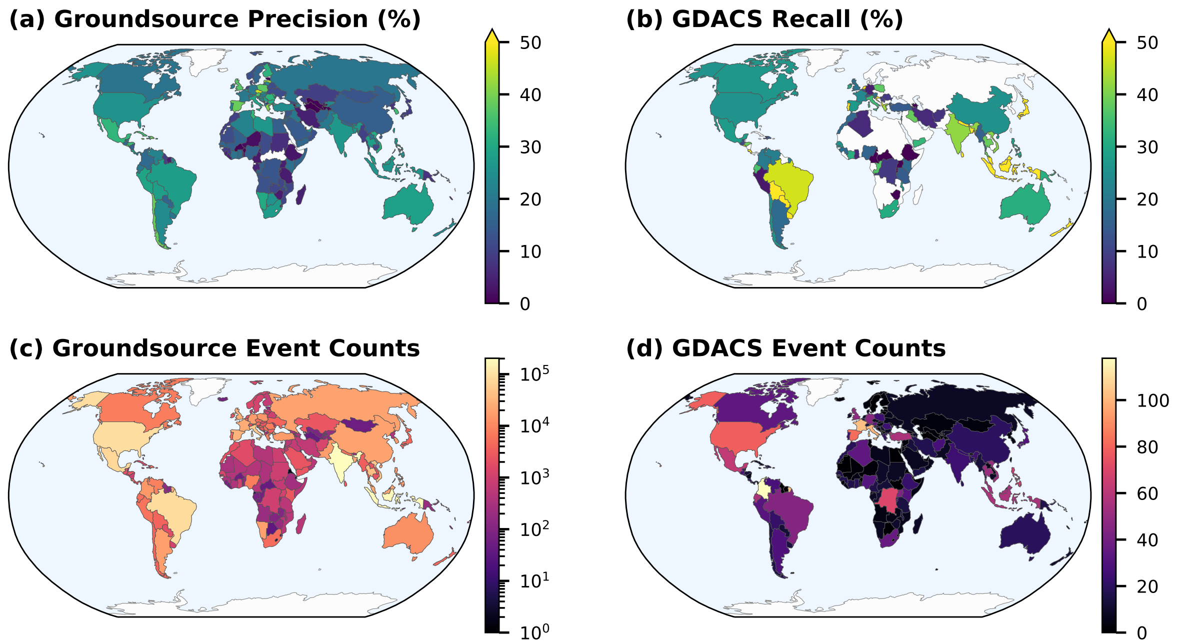

Figure 4: Map of precision (top left), recall (top right), event count according to Groundsource (bottom left), and event count according to GDACS (bottom right) by country. We exclude countries with less than 10 ground truth events, as their metrics would be very noisy. For a clear visual display, we limit the precision and recall color scale to 50%.

4 Conclusion

The results presented here demonstrate that AI-driven forecasting can achieve operational-grade performance for urban flash floods at a global scale, even in the absence of dense local instrumentation. By shifting the paradigm from local calibration against physical sensors to learning from a global ground truth dataset extracted from millions of news articles, we have overcome a primary barrier to expanding early warning systems to the Global South.

Our benchmark against the U.S. National Weather Service reveals that the AI-based model achieves results that are close to established local expert systems. Achieving performance metrics comparable to such a sophisticated, instrumentation-rich framework demonstrates how AI can bridge the warning gap in underserved regions that lack equivalent infrastructure.

While the system represents a significant advance, technical constraints remain. For example, the current spatial resolution of $0.2° \times 0.2°$ is primarily driven by the granularity of globally available atmospheric data, and improvements in meteorological forcings could further enhance localized precision. Additionally, we expect the Groundsource dataset to improve in the future, as LLMs will get better at classifying events and extracting spatiotemporal information. These improvements will directly translate into better training and evaluation data, which would in turn benefit the flash flood forecasting system. Specifically, we expect that better Groundsource data will allow us to expand coverage and relax the current constraint of highly populated areas, but also to better distinguish different types of floods.

Overall, this work highlights the potential for AI to leverage new sources of information, bridge the global warning gap, and to provide critical tools that help protect vulnerable communities from the escalating threat of flash floods.

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Author contributions

OZ designed the model. OZ and IZ conducted the core research for the project. GN and SV contributed to the initial research regarding the utility and requirements of an operational flash flood forecasting system. HF and GL contributed to the design of the operational system, which was then implemented by RM, HF, AN, and IZ. OZ, MG, and DC drafted the manuscript. All authors contributed to the critical revision of the manuscript and approved the final submitted version.

Competing interests

The authors declare no competing interests.

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A Hyperparameters

Table 1 lists the hyperparameters of the architecture used in the flash flood prediction model.

Hyperparameter	Value
L2 regularization	3e-3
Activation	ReLU
Output activation	Sigmoid
Attributes embedding layers	[32, 16, 4]
Forcing embedding layers	[16, 16]
LSTM hidden size	128
Fully connected head layers	[16, 1]
Learning rate schedule	Exponential decay with decay rate of 0.999 every 500 steps
Initial learning rate	1e-5
Batch size	256
Epochs	40
Update steps per epoch	1500

Table 1: Model hyperparameters.