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BirdNet-AI: Spatio-Temporal Modeling of Nocturnal Bird Migration Using Weather Radar and Graph Neural Networks

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Abstract: *Most nocturnal bird migration takes place beyond direct visual observation, but moving flocks leave measurable signatures in weather-radar records. BirdNet-AI was developed to turn these records into spatially continuous estimates of migration over the United States. NEXRAD scans were organized as multi-channel images and passed to a U-Net that separated likely bird echoes from precipitation and background returns. On the benchmark images, the model reached an F1-score of 85.1%, a small improvement over MistNet. The resulting station-level estimates were then analyzed with a graph neural network. Its prediction errors were 0.138 for MAE and 0.189 for RMSE, with wind speed and temperature improving performance over migration history alone. The mapped results were strongest along central and eastern flyways and showed the expected seasonal reversal between spring and fall. These findings suggest that radar-image segmentation and network-based forecasting can be combined for broad-scale migration monitoring, although the estimates remain dependent on radar coverage and labeling quality.*

Keywords: *Bird Migration, Weather Radar, Graph Neural Networks, Radar Signal Classification, Spatio-Temporal Modeling*

1. Introduction

Nocturnal migration presents an awkward observation problem: the movement is extensive, brief at any one location, and largely invisible from the ground. Counts made at field sites remain valuable, but they cannot describe a whole continent at the same time. Weather radar fills part of this gap because biological targets are recorded repeatedly over a wide area. Long radar archives can therefore reveal when migration begins, where it concentrates, and how those patterns shift from one season to another.[1][2]

NEXRAD was designed for meteorological surveillance rather than wildlife monitoring, so its records are not ready-made bird observations. Birds, bats, insects, precipitation, and ground clutter may appear in the same scan.[4] Reflectivity, radial velocity, and spectrum width help distinguish these returns, yet no single variable is decisive. A second difficulty is spatial: treating each radar independently ignores the fact that a migration front may pass through several neighboring stations in sequence.[3]

The work addresses these two problems separately. First, a U-Net identifies likely bird echoes within each radar image. Second, a graph neural network relates one station to nearby stations and predicts the next observation period. The analysis also tests whether wind and temperature add useful information, and whether the final maps resemble established flyways rather than arbitrary spatial patterns.

2. Methods

2.1. System Overview

The workflow has six linked stages, shown in Figure 1. Raw scans are cleaned and resampled before bird echoes are segmented. Echo masks are then summarized at the station level. In the graph, each radar is a node and nearby radars are connected by geographic distance. Forecasts, national heatmaps, and seasonal summaries are produced from the same station-level series.

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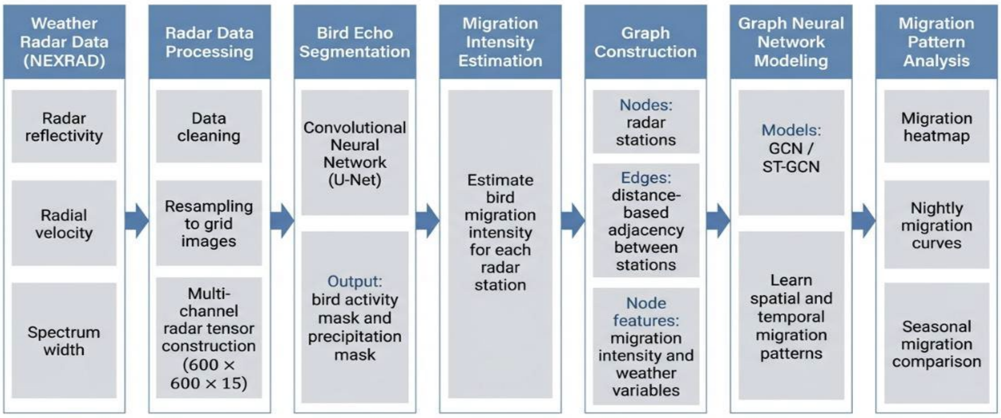

Figure 1: Overview of the BirdNet-AI pipeline for radar-based bird migration monitoring.

2.2. Data and Preprocessing

The data set contains NEXRAD Level II scans from about 160 WSR-88D stations across the United States.[4] The selected period, 2015-2023, includes reflectivity, radial velocity, and spectrum width at several elevation angles. Wind speed and air temperature from the National Climatic Data Center were matched to the radar timestamps.[7] Table 1 summarizes the coverage and the variables retained for analysis.

Table 1: Radar and meteorological data used in the study.

Attribute	Description
Radar network	NEXRAD across the United States
Number of stations	Approximately 160
Radar variables	Reflectivity, radial velocity, spectrum width
Temporal resolution	Approximately 4.5-10 minutes per scan
Spatial coverage	Approximately 230 km around each station
Study period	2015-2023
Meteorological variables	Wind speed and temperature

Scans with obvious corruption were discarded, and persistent background interference was removed. The remaining polar observations were resampled to 600 x 600 Cartesian grids. Three radar variables at five elevation angles produced 15 channels for each time point. Figure 2 shows this conversion from the original scan to the tensor supplied to the segmentation model. Predicted bird pixels were later pooled to obtain one migration-intensity estimate per station and observation period.

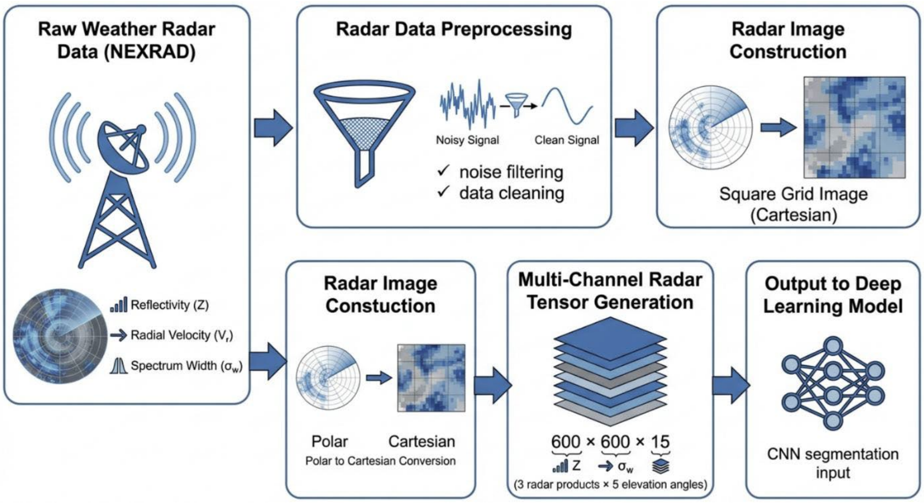

Figure 2: Radar-data processing pipeline for constructing multi-channel tensors from NEXRAD observations.

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2.3. Learning Models

Bird-echo segmentation used the encoder-decoder network in Figure 3.[5] Its skip connections return fine spatial detail to the decoder after features have been compressed, which is useful for irregular echo boundaries. Training and evaluation used annotated radar images from the MistNet benchmark; biological echoes were labeled separately from precipitation and other returns.[8]

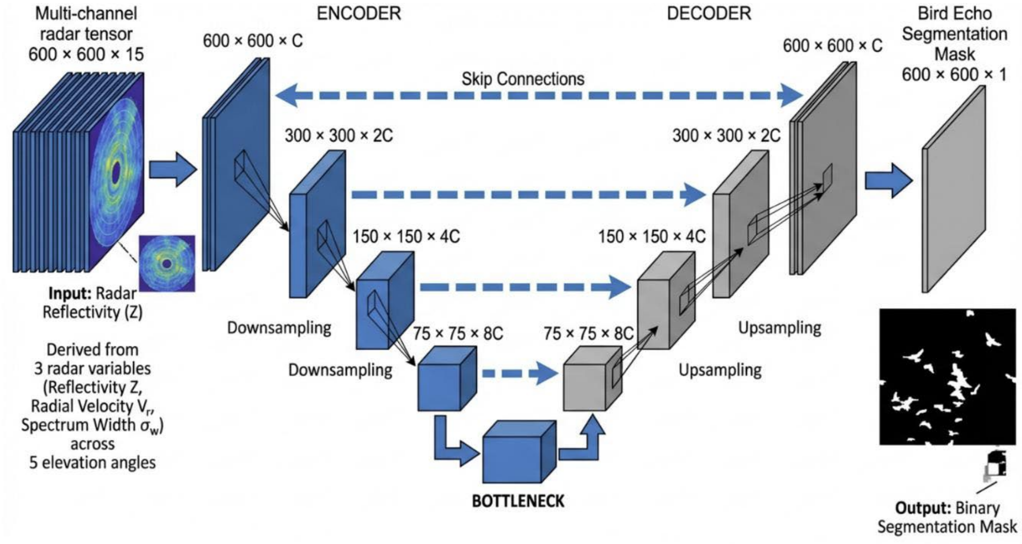

Figure 3: U-Net architecture used for bird-echo segmentation.

For forecasting, each radar became a graph node carrying migration intensity, wind speed, and temperature. Edges joined geographically close stations. The graph network combined a station's recent record with information from its neighbors before predicting the next time step.[6] In this way, a moving front could influence successive stations instead of being modeled as a set of unrelated local events.

3. Results

3.1. Segmentation Performance

Table 2 reports the segmentation results. U-Net reached 84.7% precision, 85.6% recall, and an F1-score of 85.1%; MistNet reached 82.0% on the same F1 measure.[8] The U-Net masks also recorded 74.2% IoU and an 85.0% Dice score. The numerical gain is not large, but the examples in Figure 4 show why it matters: narrow or uneven bird-echo regions are retained while much of the non-biological return is removed.

Table 2: Segmentation performance comparison.

Model	Precision	Recall	F1-score	IoU	Dice
MistNet	81.4	82.7	82.0	-	-
U-Net (proposed)	84.7	85.6	85.1	74.2	85.0

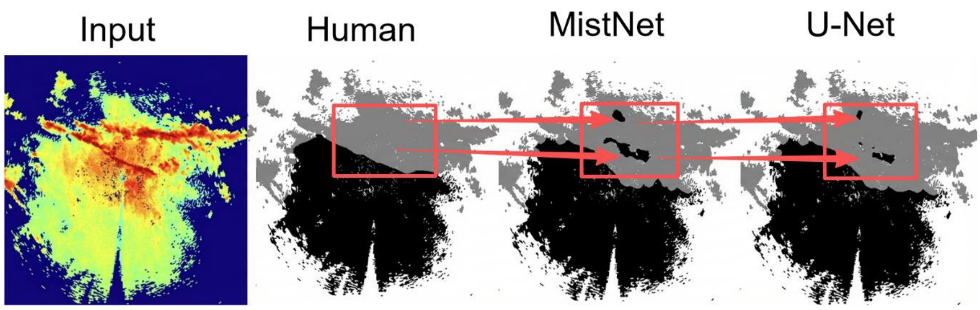

Figure 4: Qualitative comparison of bird-echo segmentation using human annotation, MistNet, and U-Net.

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3.2. Migration Prediction

The graph model gave the lowest errors in Table 3: 0.138 MAE and 0.189 RMSE, compared with 0.314 and 0.487 for the historical mean. Linear regression fell between the two. Table 4 then separates the contribution of the meteorological inputs. Migration history alone produced an MAE of 0.156; wind reduced it to 0.145, temperature to 0.147, and the two variables together to 0.138. Thus, neither weather variable accounts for the entire improvement, but both supplied information that was absent from the station history.

Table 3: Migration prediction performance.

Model	MAE	RMSE
Historical Mean	0.314	0.487
Linear Regression	0.273	0.331
GNN (proposed)	0.138	0.189

Table 4: Ablation study of meteorological node features.

Node features	MAE	RMSE
Migration intensity only	0.156	0.213
Migration intensity + wind speed	0.145	0.198
Migration intensity + temperature	0.147	0.201
Migration intensity + wind speed + temperature	0.138	0.189

3.3. Spatial and Seasonal Patterns

The national map in Figure 5 is not spatially uniform. Higher values extend through the central and eastern United States, with a pronounced band along the Mississippi corridor and into the Southeast. Much of the West is weaker. This east-central concentration broadly follows the Mississippi and Atlantic flyways described in earlier migration studies.[9]

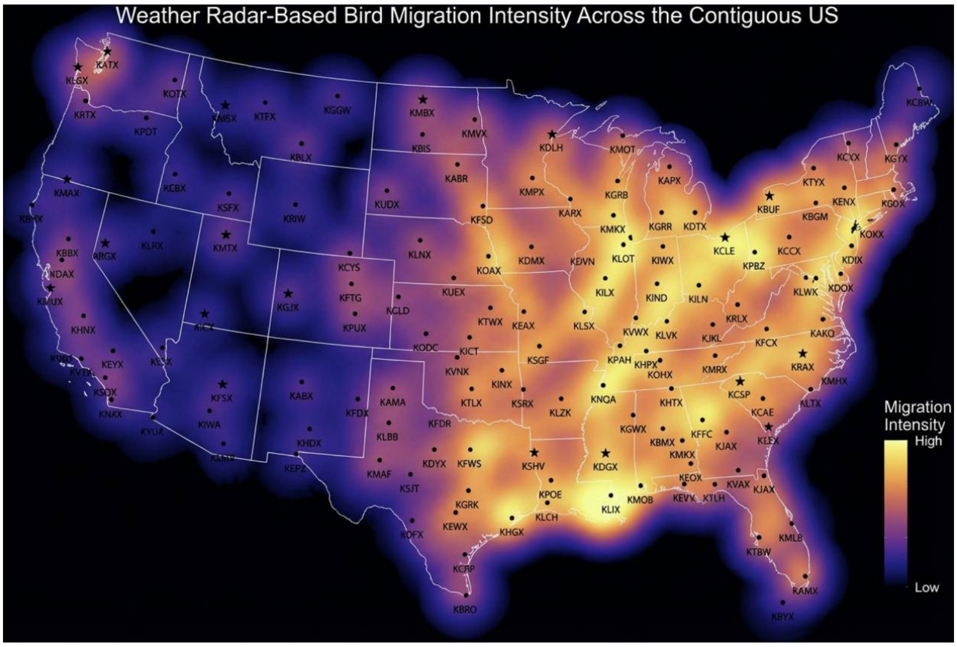

Figure 5: Spatial distribution of bird migration intensity across the contiguous United States.

Averaging by season reveals a second pattern. As Figure 6 shows, spring activity runs northward from the Gulf Coast and Southeast, whereas the fall distribution shifts south from the Midwest and Great Lakes. The contrast is consistent with the continental change in nocturnal migration phenology reported by Horton and colleagues.[10]

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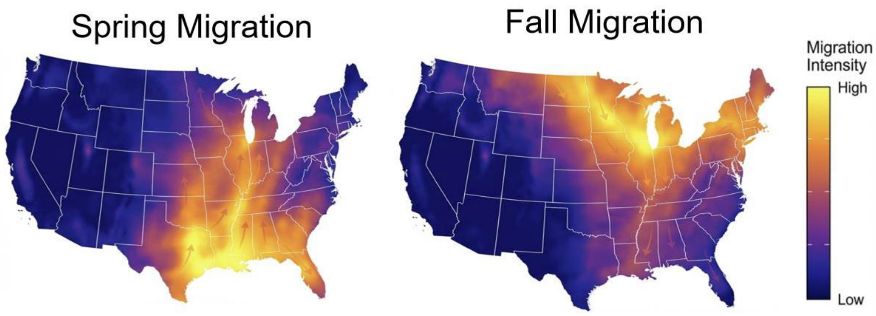

Figure 6: Seasonal comparison of spring and fall bird-migration intensity.

4. Discussion

The segmentation and forecasting stages solve different errors in the observation chain. U-Net works within a scan, where the main problem is separating biological structure from weather and clutter. The graph model works between stations, where the problem is deciding whether nearby changes belong to a larger moving pattern. The improvement over MistNet is modest, so it should not be read as a wholesale replacement of the benchmark. It does, however, suggest that the multi-scale U-Net representation is helpful at irregular echo boundaries.[8]

The forecasting comparison points in the same direction. A station's recent history is useful, but neighboring stations carry additional information about an approaching or departing migration front. That is the practical advantage of graph aggregation over an independent linear model.[6] Wind and temperature further reduce error, which is plausible given the known role of atmospheric conditions in migration timing and flight cost.[3] The ablation in Table 4, however, also shows that these weather effects are incremental rather than dominant.

The maps offer a useful plausibility check rather than an independent validation. Their central and eastern concentration resembles known flyways,[9] and the spring-fall reversal follows the documented continental timing of migration.[10] Agreement at this scale reduces the likelihood that the model is responding only to fixed radar artifacts, although station-level ecological validation is still needed.

Several limitations remain. Radar cannot identify species directly, and residual insect, precipitation, or clutter echoes may survive the segmentation step. The benchmark labels are also imperfect, especially near ambiguous echo boundaries. Coverage is densest where NEXRAD stations are plentiful, so confidence should be lower in sparsely monitored regions. A stronger evaluation would hold out entire years and geographic regions, not only individual images. It would also compare station estimates with independent field observations. Longer sequences and additional variables such as precipitation, pressure, and wind direction are reasonable next steps, but species-level inference will require ecological data beyond weather radar.

5. Conclusion

BirdNet-AI links two tasks that are often handled separately: identifying bird echoes in radar images and following their movement across a network of stations. In this evaluation, U-Net slightly improved segmentation over MistNet, while the graph model reduced short-term prediction error relative to historical and linear baselines. Wind and temperature added smaller but measurable gains. The resulting maps followed recognizable flyways and seasonal directions, which supports further testing of the approach. The present results should nevertheless be treated as broad migration estimates, not species-level observations or a substitute for field monitoring.

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