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Artificial Neural Network Approach for River Flow Forecasting

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RESEARCH ARTICLE

Abstract

Predicting river flow velocity is important for managing water resources, reducing flood risks, and supporting environmental monitoring. Conventional measurement techniques frequently rely on manual labor or physical sensors, which can be expensive and challenging to maintain. This work estimates surface water velocity as a simpler, contactless solution using a video-based approach. Two videos were shot from various perspectives: a side view at ground level and a top-down view with a drone. Motion between video frames was detected using the Farneback Optical Flow approach, and the motion was translated into velocity measurements. After that, the data was standardized and smoothed to enhance the prediction outcomes. Short sequences of past values were used to train an Artificial Neural Network (ANN) to predict the next velocity value. ANN was chosen due to its straightforward design, quick training time, and ability to handle non-linear data patterns. The model was trained and evaluated on both videos to see how the video angle influences performance. Top-down drone footage resulted in higher forecast accuracy. Although the system is not yet real-time, this study demonstrates the possibility of merging video processing and artificial neural networks for future river flow monitoring.

Keywords: river flow velocity; video-based monitoring; artificial neural network; surface water prediction; aerial video analysis

1. Introduction

Effective management of water resources, environmental protection, and flood control works rely on accurately predicting river flow velocity. Reliable prediction could alleviate the impacts of extreme weather, infrastructure planning, mitigation measures, and ecological conservation. Rivers, however, are complex systems impacted by rainfall, land use, channel morphology, and more, which makes it challenging to accurately predict the river network's future with existing hydrological models.

Conventional hydrological models, such as conceptual and physics-based approaches, often rely on one-dimensional datasets and simplified assumptions, limiting their ability to capture the

complex, nonlinear interactions between rainfall, runoff, and river flow under varying climatic conditions. Furthermore, conventional techniques including deterministic systems are characteristically subjected to simplifying assumptions and interpretations, failing to effectively capture the nonlinear and dynamic nature of river growth. As a consequence, machine learning and data-driven methods have been increasingly explored to enhance the accuracy and efficiency of hydrological forecasts.

ANN – Artificial Neural Networks are machine learning models that roughly take the inspiration of how the human brain functions. They are good at finding patterns and relationships that exist in data even if those patterns are complex and non-linear. ANN have been widely used in various fields and have been demonstrated to be successful in terms of streamflow and rainfall-runoff prediction (Liu et al., 2021; Zhang et al., 2022). In river flow modeling, ANN can be trained to learn from past data and predict future values without needing detailed knowledge of the physical system.

Compared to more advanced deep learning models like Long Short-Term Memory (LSTM) networks, ANN is simpler and faster. While Mehedi et al. (2022) praised LSTM for its ability to handle long-term time series dependencies, ANN excels in the presence of well-preprocessed data, especially when short-term trends are strong enough. This makes ANN especially appealing as a quick, practical solution in data-scarce or resource-limited areas.

This research uses Artificial Neural Networks (ANN) to predict river flow velocity using video footage, focusing on how ANN interprets visual data to predict water velocity. The flow velocity data are extracted from video footage via drone optics using Optical Flow methods. The goal is to demonstrate the feasibility of ANN technology to manage water resources.

2. Literature Review

Artificial Neural Networks (ANN) have been widely studied and applied in the field of hydrological forecasting, particularly due to their strength in capturing complex, non-linear relationships in data. Their strength in modeling non-linear time series has also been demonstrated in broader forecasting research, where ANN outperformed many traditional statistical approaches (Khashei & Bijari, 2009). Unlike traditional hydrological models that depend heavily on physical parameters and assumptions, ANN operates as a data-driven model, making it a suitable choice for modeling dynamic systems like river flow, where complete physical data may be unavailable.

According to Liu et al. (2022) ANN have been shown to have favourable accuracy in streamflow forecast, particularly when performed with well conditioned input data. This performance is driven by its capacity for historical learning and trend prediction under non-linear system dynamics. ANNs are extensively utilized in the applied sciences to bypass the limitations of traditional physical models that depend on restrictive simplifying assumptions, particularly when dealing with highly dynamic systems involving damped vibrations and sudden variations in load.

Zhang et al. (2022) further noted that ANNs are capable of achieving robust performance with a low level of model complexity, particularly concerning rainfall-runoff modeling. The study discussed how ANNs, if properly calibrated, could outperform more sophisticated systems in terms of their computational time and memory requirements. This attribute is particularly beneficial for tasks that need to be completed quickly, or for systems that need to be monitored in real time.

Compared to deep learning techniques, such as Long Short-Term Memory (LSTM) networks, ANNs are easier to teach and much more straightforward. LSTM networks are tailored for long-term dependencies in sequential data. Thus, they are more appropriate for time series data that require a longer memory or involve more pronounced lagged effects. However, ANNs perform well in cases in which the majority of the necessary data for prediction has recently been acquired and the dataset has been appropriately smoothed or pre-processed (Mehedi et al., 2022).

In addition, video-based hydrological approaches have gained popularity in recent years. Jyoti et al. (2023) demonstrated that image processing techniques such as Optical Flow may be utilized to estimate surface water velocity using video frames. Once the velocity data has been extracted, machine learning models such as ANN can be used to forecast future flow behavior.

Overall, the literature shows that ANN is a reliable and computationally efficient model for river flow prediction, particularly when applied to data extracted from videos.

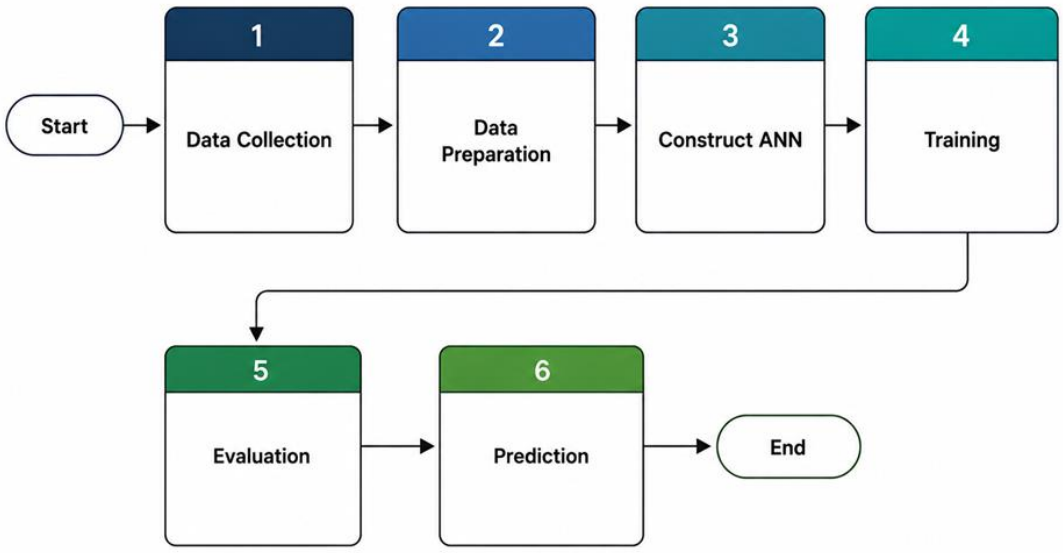

Figure 1: Flowchart for river flow velocity prediction

As illustrated in Figure 1, its flexibility, simplicity, and proven accuracy make it an appropriate choice for this study, where river surface velocity is predicted based solely on visual inputs processed using Optical Flow.

3. Methodology

This study utilized an Artificial Neural Network (ANN) to estimate river flow velocity based on surface velocity vectors extracted from video recordings. The methodological steps include video data collection, preprocessing and velocity extraction, data smoothing and normalization, and model development. The goal was to evaluate the ANN's ability to forecast surface velocity trends using only video-derived data.

3.1 Data Collection

The video dataset used in this study was provided by I-Net Spatial Sdn. Bhd., consisting of two high-resolution video files:

- **DJI_0723_30.mp4**: A ground-level video showing the river flow from a near-horizontal viewpoint, lasting approximately 1 minute.
- **DJI_0724.mp4**: A drone-captured aerial video, recorded from a top-down perspective, approximately 12 seconds in duration.

Both videos were recorded at a frame rate of 30 frames per second (FPS) with a resolution of 720 × 480 pixels, which was retained for consistency throughout the processing stages. These two perspectives provided different views of the river's surface movement, which is crucial for evaluating the adaptability of the ANN model to diverse visual inputs.



Figure 2: Ground-level Video



Figure 3: Top-down Video

3.2 Region of Interest (ROI) and Frame Extraction

Each video was divided into individual image frames to prepare them for motion analysis. A Region of Interest (ROI) was manually selected within the frames. The selected ROI included the portion of the river where water movement was most visible and consistent across frames.

Manual adjustments were made until the ROI produced stable and accurate tracking results when tested using motion analysis techniques. By isolating the ROI, irrelevant background movement (e.g., vegetation, reflections) was excluded, improving the quality of the motion vectors extracted later.

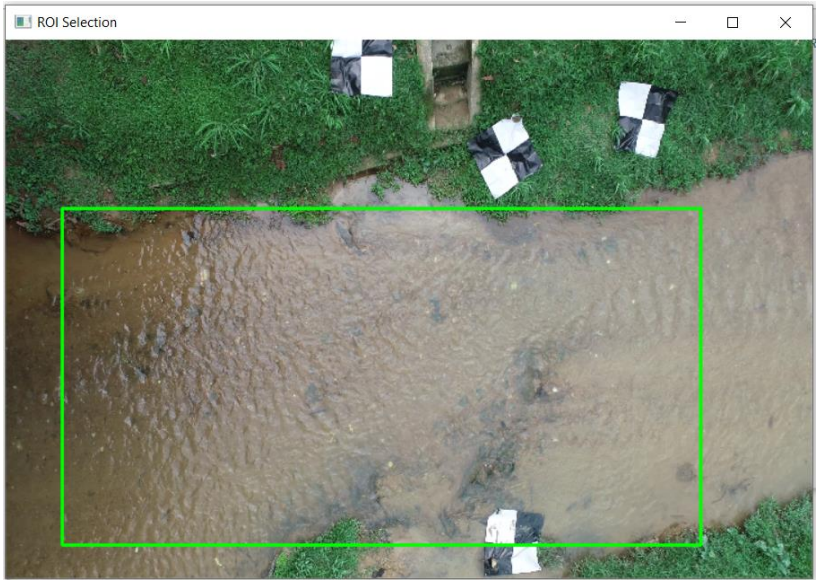

Figure 4: ROI Adjustment

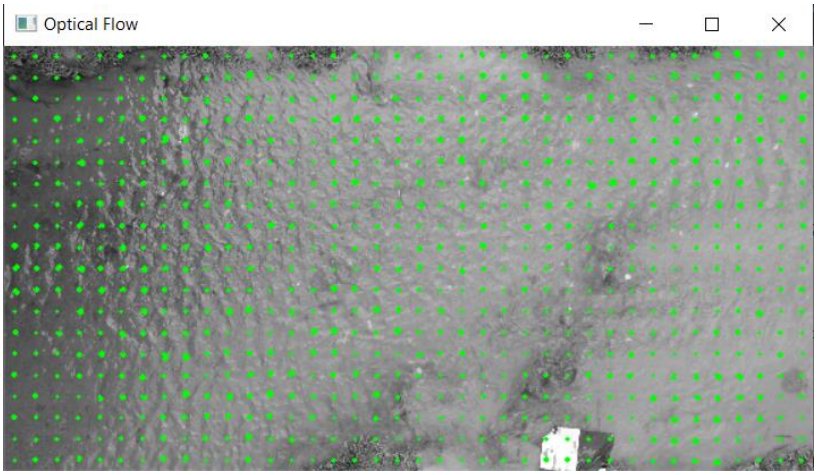

Figure 5: Selected ROI for Optical Flow Processing

3.3 ANN Model Development

The ANN model was developed within the Keras framework running on TensorFlow. The model structure included:

- A Flatten layer that transformed the 5-dimensional input sequence into a 1-dimensional vector.
- A Dense layer featuring 64 neurons with ReLU activation.
- A second Dense layer containing 32 neurons with ReLU activation.
- An Output layer with a single neuron for predicting the velocity.

The model was compiled with the Adam optimizer and Mean Squared Error (MSE) as the loss function. Following established practices for models of this type, the model was trained for 50 epochs with a batch size of 16 (Liu et al., 2021).

3.4 Model Evaluation

To establish the model's confidence for calculating river flow velocity, look into the predicted performance. A number of statistical metrics were used to assess the accuracy of estimated values in

relation to real river flow velocity, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). According to Moriasi et al. (2007), these assessment criteria are often employed in hydrological modeling to calculate deviations and error magnitudes.

- **Mean Absolute Error (MAE)**
  - MAE calculates the average magnitude of the errors in a dataset, considering only absolute differences between the predicted and actual values. It is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x^i - y^i\right| \tag{1}$$

A lower MAE value indicates a higher accuracy of the model, as it signifies smaller deviations between predictions and actual values (Moriasi et al., 2007).

- **Mean Squared Error (MSE)**
  - MSE is another widely used evaluation metric that calculates the mean of the squared differences between predicted and actual values. It is given by:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}\left(x^i - y^i\right)^2 \tag{2}$$

A lower MAE value indicates a higher accuracy of the model, as it signifies smaller deviations between predictions and actual values (Moriasi et al., 2007).

- **Root Mean Squared Error (RMSE)**
  - RMSE is the square root of MSE and provides an estimate of error magnitude in the same unit as the predicted variable:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x^i - y^i\right)^2}{n}} \tag{3}$$

When determining how closely the model predictions match the actual river flow velocity estimates, RMSE is critical. A lower RMSE indicates a more accurate model, whereas a greater RMSE indicates more deviations (Moriasi et al., 2007).

4. Results and Discussions

This section presents the performance of the ANN model using video-derived data. Two datasets, one aerial (drone) view and one ground-level view were utilized to train and evaluate the model. The predictor variables fed into the ANN were the pixel velocity values extracted from these videos via Optical Flow. To assess estimation accuracy and consistency, the findings are presented both graphically and numerically.

4.1 Data Smoothing and Normalization

The velocity time series often displayed sudden fluctuations due to lighting changes, turbulence, or noise in video frames. To handle this, a moving average filter with a window size of 5 was used. This filter helped smooth out high-frequency variations and emphasized the main flow trend across time.

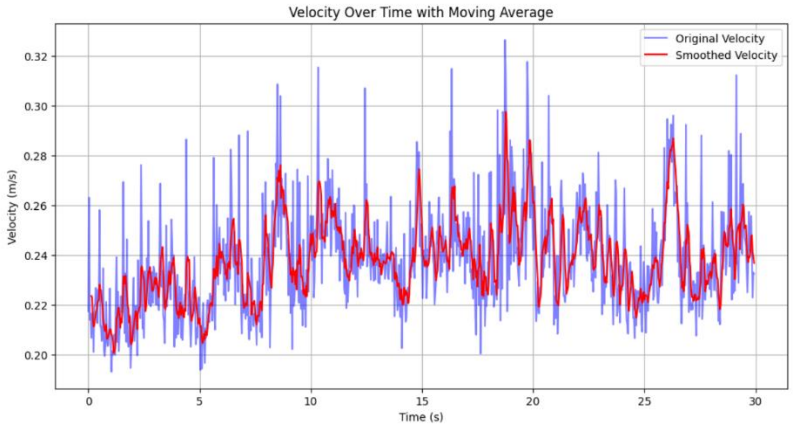

Figure 6: Smooth Velocity from ground-level video

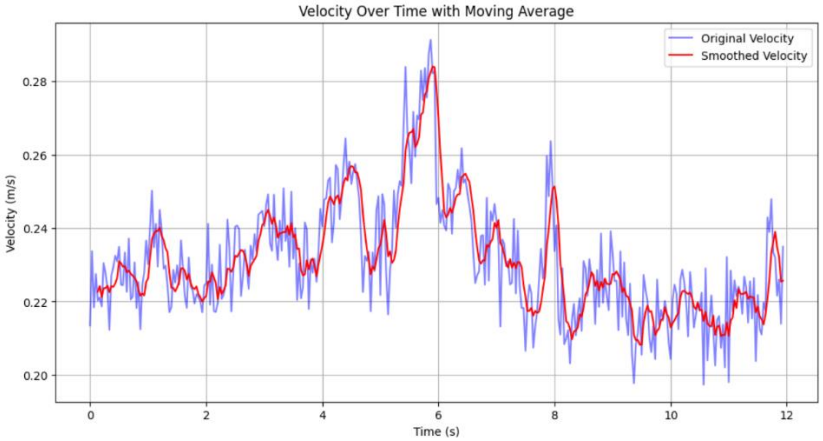

Figure 7: Smooth Velocity from top-down video

After smoothing, the data was normalized using the MinMaxScaler approach, which scales all values from 0 to 1. This normalized phase is crucial in neural network training because it ensures that no input value dominates and accelerates shift during optimization (Zhang et al., 2022). Given that the optical flow values represent steady, continuous surface motion patterns within a predictable range, Min-Max scaling effectively preserves the linear relationships between the inputs without distortion.

4.2 Prediction Visualization

The ANN model was trained and evaluated separately for each video. The prediction results were plotted against the smoothed actual velocity values to visualize the model's performance in tracking flow patterns.

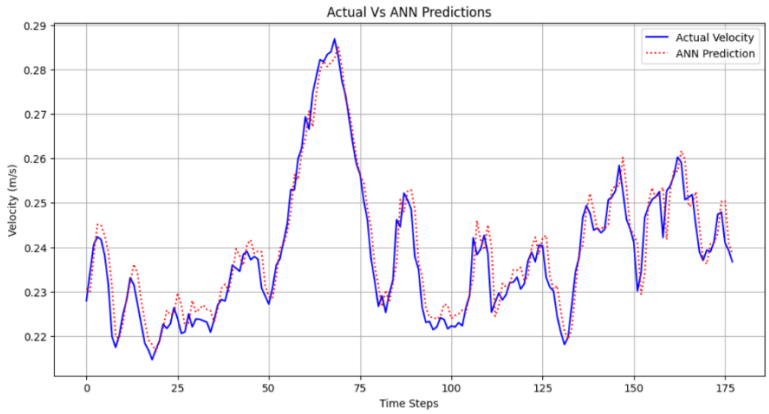

Figure 8: Predicted result from ground-level (DJI_0723_30)

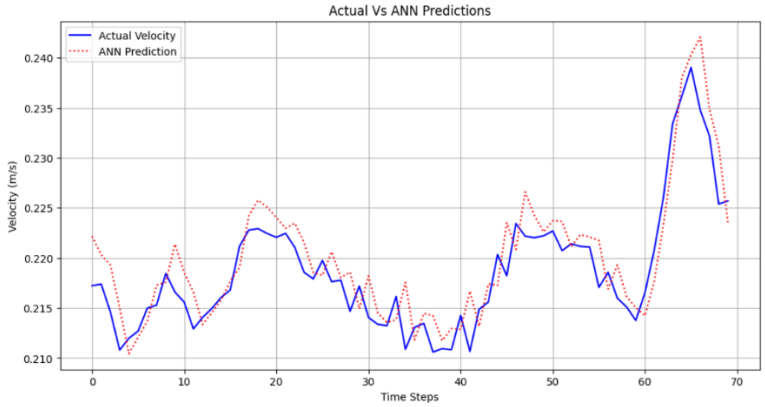

Figure 9: Predicted result from top-down (DJI_0724)

The ANN model was able to track the general patterns in both datasets, as can be seen from the plots. But because the top-down view of the river flow was more clear, the predictions from the drone view (DJI_0724) seemed smoother and more in line with the actual values. Predictions in the ground-level video (DJI_0723_30) varied considerably, presumably as a result of background noise and impediments in the side-view visibility of the sea surface.

4.3 Performance Evaluation

The performance of the ANN model was evaluated using the following error metrics:

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)

Table 4.1: ANN performance matrics for both video

Dataset	MAE	MSE	RMSE
DJI_0723_30	0.0040	0.0000261	0.0051
DJI_0724	0.0022	0.0000071	0.0027

The visual outcome that the predictions from this dataset were more stable is supported by the ANN model's lower error values on the drone footage (DJI_0724). This implies that for motion-based velocity estimation, aerial views offer cleaner input signals.

Considering the limited sequence context and the lack of additional environmental variables like rainfall or water level, the ANN model showed high prediction performance on both datasets despite its simplicity.

4.4 Discussion

When forecasting river surface velocity using video-derived data, the ANN model demonstrated an acceptable level of accuracy. Compared to models like LSTM, which rely on time-dependent memory structures, its performance was particularly significant because it only employed single-variable input and short-term sequences.

The outcomes support the literature's findings (Liu et al., 2021; Zhang et al., 2022) that artificial neural networks (ANNs) are useful for hydrology's short-term forecasting tasks, particularly when the data have been smoothed and preprocessed. While the drone view offered more reliable input for the ANN to learn from, the ground-level video presented more difficulties because of background interference.

Even though ANN doesn't have the sequential memory of LSTM, it's still a lightweight and useful option for velocity prediction because of its quick training and almost accurate results, especially when basic patterns are retrieved from brief video sessions. Even though this study was carried out offline, the methodology has the potential to be used in real-time in the future with more system integration.

5. Conclusion

This study explored the use of an Artificial Neural Network (ANN) to predict river flow velocity based on data extracted from video recordings. The approach involved collecting videos from two different perspectives, extracting surface velocity using Optical Flow techniques, and training a feedforward ANN model with smoothed and normalized velocity values.

The results showed that the ANN model was capable of learning the short-term flow patterns and producing accurate predictions, especially when applied to video data with a clear top-down perspective. Quantitative performance metrics such as MAE, MSE, and RMSE confirmed that the ANN achieved low prediction errors on both datasets. The drone-captured video (DJI_0724) yielded better results, suggesting that the viewing angle and input quality significantly influence prediction performance.

ANN was chosen in this study for its simplicity, ease of implementation, and computational efficiency. Although it does not include time-dependent memory like LSTM, it still proved effective for short-term forecasting when the input data were properly prepared. This supports findings from previous studies that ANN is suitable for hydrological modeling tasks where data relationships are non-linear but relatively short in temporal scope (Liu et al., 2021; Zhang et al., 2022).

While the current model was tested in an offline environment, it demonstrates the potential for future integration into automated monitoring systems using video data. Further work may include real-time deployment, testing with more diverse datasets, or combining ANN with other techniques to improve generalization.

In summary, the ANN-based approach provides a promising foundation for video-based velocity prediction in river systems, especially in contexts where simplicity, speed, and interpretability are important.

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