

Implementing Inertial Navigation Systems in Wearable Devices using Machine Learning				
Domain: IoT, Sensor Intelligence, and Machine Learning Applications				
<b>Abstract:</b> Wearable devices struggle to provide reliable navigation when GNSS signals degrade or disappear, causing pure inertial tracking to accumulate large drift due to noise and bias in low-cost MEMS sensors. This project addresses this problem by developing a GPS-independent inertial navigation framework that fuses Kalman-filtered sensor preprocessing with lightweight machine-learning models for accurate position estimation in GNSS-denied environments. The system first stabilizes raw accelerometer, gyroscope, and magnetometer data using a Kalman filter, producing drift-reduced motion features. Multiple deep learning baselines (LSTM, ResNet-1D, Transformer) were evaluated against proposed hybrid recurrent–ensemble architectures—GRU-SVR, GRU-XGBoost, and BiGRU-XGBoost. Experiments on smartwatch-collected IMU data show that while Transformer performs best among generic models with a drift of 403.8 m/km, hybrid methods achieve far superior accuracy. The proposed GRU-XGBoost model reduces positional drift from 162.6 m/km (GRU-SVR) to just 16.3 m/km (a tenfold improvement), achieves average distance error below 0.009 m, RMSE in the order of 10, and maintains real-time inference latency under 3 ms. These results demonstrate that combining temporal feature encoding with gradient-boosted nonlinear regression significantly enhances drift suppression while remaining efficient for on-device wearable deployment. The framework offers a practical pathway for continuous pedestrian localization, emergency responder tracking, and fitness analytics in environments where GNSS is unavailable or unreliable.				
<b>Architecture / Flow Diagram:</b> <div><p>INS Based GPS Prediction System with Kalman Filtering &amp; ML Model</p><pre>graph TD     subgraph Smartwatch         IMU[IMU Sensors&lt;br/&gt;(Accelerometer, Gyroscope,&lt;br/&gt;Magnetometer)]         GPS[GPS Sensor]     end     subgraph EdgeProcessing         SP[Sensor Preprocessing]         KF[Kalman Filter]         PE[Position Estimation]     end     subgraph ML_Model [Machine Learning Model]         ML[ML Model]     end     subgraph Application_Layer [Application Layer]         PGO[Predicted GPS Output]         UI[User Interface]     end     subgraph Memory_Bank [Memory Bank]         PIMU[(Past IMU/GPS Data)]     end      IMU -- "Collects Motion Data" --&gt; SP     GPS -- "Provides GPS data (if available)" --&gt; KF     SP -- "Sends Processed IMU Data" --&gt; KF     KF -- "Corrected Sensor Data" --&gt; PE     PE -- "Sends Refined Data for prediction" --&gt; ML     ML -- "Predicts coordinates" --&gt; PGO     PGO -- "Displays estimated position" --&gt; UI     PIMU -- "Fetch old data for refinement" --&gt; ML     ML -- "Provides historical data for prediction" --&gt; PIMU     PIMU -- "Updates Model with new data" --&gt; ML     PIMU -- "Store and retrieve data" --&gt; KF</pre></div>				
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