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# TRAJECTORY INTERCEPTION CLASSIFICATION FOR PREDICTION OF COLLISION SCOPE BETWEEN MOVING OBJECTS

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**Abstract.** In the fields of autonomous navigation and vehicle safety, accurately predicting potential collision field points between moving objects is a significant challenge. A novel computing technique to enhance trajectory interception analysis is presented in this paper. Our objective is to develop a field model that can accurately forecast collision zones, improving road transportation safety and the use of autonomous cars. Our main contribution is a binary classification model called PCSMO (Prediction of Collision Scope between Moving Objects), which is based on zero-shot learning. Gann angles, which are typically 45 degrees, are used to analyze the trajectories of moving objects. This method is inspired by GANN (Gann Angle Numeric Nomenclature). Compared to earlier techniques, this model more accurately identifies potential collision collision interception zones. The technique computes Gann angles for trajectory analysis and extracts GPS coordinates of moving objects from video data using OpenCV. It offers a more sophisticated comprehension of object movement patterns and points of interception. To assess the precision, recall, F1-score, and prediction accuracy of our model, we employ 10-fold cross-validation. Comparing the PCSMO model to existing models, these metrics demonstrate how well the PCSMO model predicts potential collision zones. Our approach, we discovered, enhances trajectory analysis—a critical component of safer autonomous navigation systems. With potential applications in autonomous vehicle and UAV safety, the PCSMO model improves field interception classification.

**Key words:** Collision, Moving Objects. Global Positioning System, Machine Learning, Binary Classification, Gann Angle Degree, Trajectory Interception Detection, Unmanned Aerial Vehicles, Zero-Shot Learning.

**1. Introduction.** A conglomeration of advanced technological systems in combination with contemporary mobility solutions has created a paradigm shift in the ways supply chain ecosystem, and commutation systems across the world are becoming safer. There is a various set of tools, technical, management practices, and instrumentation engineering practices that are paving for safety in the mobility systems. Right from a two-wheeler to the jumbo-jet airliners at every level, the reliance on technology solutions has raised notches, and today, there are scores of control models that guard safe transportation and mobility.

Today, the contemporary practices of Unmanned Aerial Vehicles (UAVs), self-driven cars, drone-based delivery chains, robotic solutions, and AI solutions manning the traffic monitoring and control systems refer to a paradigm shift in futuristic solutions. While the scope of new-age solutions looks promising, still the scope for enhancements to the security and overall efficiency of autonomous vehicles is imperative [1].

Increasing demand for autonomous vehicles and vehicles with sensors for traffic mobility is on the rise, the systems must be more equipped in terms of mechanisms, patterns in which the systems are being deployed, and the measures that can help in improving the overall process of drive-safe conditions. In addition to the road-safety conditions with driver-less vehicles, even in the case the unmanned aerial vehicles, the role of systems in predicting the projectile path and the possible cross in the trajectory is impeccable need. As the domain is gaining traction, and the need for more comprehensive solutions are imperative, in this manuscript, the scope of developing prediction models that can be resourceful in the trajectory path crossing conditions is explored.

Projectile path trajectories estimation models are significant in the domain, and there are numerous models that were developed which could address the patterns and possible intersections. One key area wherein the studies are limited is the scope of motion analysis pertaining to a greater number of projectiles being in its motion simultaneously. However, there are a certain set of fundamental mathematical models and physics-theories-related equations and algorithms proposed earlier, which can address the projectile path conditions [2], [3]. Developing a secondary system that can create affirmative to the primary analysis approach can be a

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significant solution and embracing such solutions can lead to significant benefits for the predictive models, which can be resourceful in autonomous vehicles or UAV movement too. In this manuscript, focus is on the scope of continuous objective movement tracking and estimation of any close areas wherein the potential trajectory cross, and early stage of predictions of such trajectories [4]. Following are the key objectives considered in development of the proposed model:

- The first objective is to track the projectile path of an object in motion and its trajectory
- The second objective is to understand how the projectile path of an object can interfere with the other object in motion that is being tracked.
- Classification of the possible interceptions according to threat levels is based on the dynamic movement of the projectiles.

Targeting the above objectives, the approach in the model is to develop a systematic model wherein the key paths used by the projectiles are monitored and accordingly develop an interception mapping system that can change according to the real-time environment.

**2. Related Work.** Scores of models pertaining to object collisions on path prediction, accidents-related risk mitigation in autonomous vehicle segments, traffic density-based accident prediction zones, potential paths of gliding, and intersections are some of the actual ranges of studies explored in the literature review. From the summation of key points in the literature, the following are some of the critical observations and learnings: The majority of the trajectory-related studies or safety-related studies are reliant on third-party components or tools like sensors, GPS positioning tools, density meters, altitude meters, speedometers, etc. The performance of the whole system is dependent on the inputs attained from the equipment or tools adapted in the models. Irrespective of the efficacy of the models, any depletion in the quality of the tools used for gauging metrics could be a serious threat in terms of miscalculation and ineffective predictions of the intersections [5–11].

The other key observation is about application of the solutions for univariate analysis, like one moving object movement compared to the other static object sensors, etc. When there are more than one object making moves in zigzag or varying directions, the complexities of accuracy are high for the predictive models [12–16].

"COLLIDE-PRED," developed by Author et al. [17], uses the motion of objects moving to provide collision predictions. It is a pipeline that begins with object identification, which is utilized for object tracking; afterwards, trajectory prediction is conducted, which culminates in collision detection. The authors indicated that the COLLIDE-PRED will determine the probable site of the collision. This model attempted to determine the target object's trajectory's collision scope, which often exhibits false alarm. In addition, the collision scope of moving objects can only be predicted using this approach for offline video streams.

Applying the machine learning model is seen as a promising solution from the literature towards testing the label classification approach and other such metrics, which are significant for the execution of the models. There are scales of statistical and technology-centric models discussed in the literature towards understanding the scope of autonomous vehicle safety in its trajectory. However, there is a need for more explorative studies in the domain to improve the overall efficiency with which the solutions can be managed. In order to address the constraints addressed in this review of contemporary literature, this manuscript suggests a novel zero-shot binary classification model that discovers threat zones and safe zones of trajectory interceptions.

In the further sections of this manuscript, Section 2 refers to the related work summary from the literature review. Section 3 provides insights into the materials and methods, the proposed model narrative, its algorithm flow, and other key metrics that signify the mode. Section 4 provides insights into the experimental study, and Section 5 refers to the conclusion based on the efficiency aspects estimated from the model.

**3. Proposed Method and Materials.** The method of classifying trajectory interceptions with and without collision scope between moving objects and respective materials have been explored in this section. The section includes the narrative of the suggested model. By uniquely combining zero-shot learning with GANN principles, the PCSMO (Prediction of Collision Scope between Moving Objects) predictive model presents a novel approach to collision detection. Unlike traditional models, the PCSMO model can reliably predict collision points without historical data thanks to this integration. The key to this innovation is the application of Gann angles, which are used in financial markets, to trajectory analysis. These angles provide a new perspective on trajectory interception classification by enabling the PCSMO model to predict collision points in dynamic

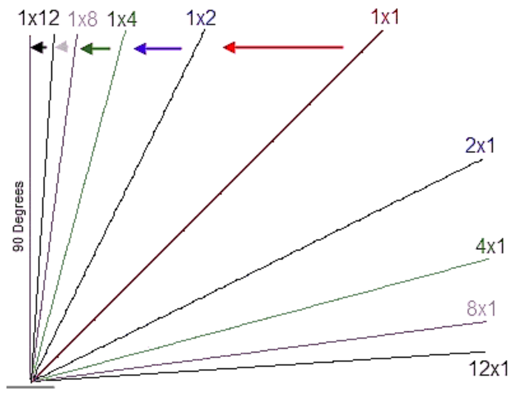


Fig. 3.1: The Gann angle degree

scenarios such as road traffic and autonomous vehicle navigation. In order to improve Gann angle calculations, the model additionally makes use of OpenCV to extract precise GPS coordinates from video data. This approach adds something uniquely to the field of trajectory analysis while improving the predictive power of the model.

**3.1. Model Narrative.** The model proposed in this manuscript is based on the trajectory detection requirements, and fundamentally the concept of Gann Theory is used in the development of the model. While the metrics and techniques used in the assessment of the path and motion are prevalent in many of the earlier studies, application of GANN angle formations is a unique concept explored in this manuscript.

Gann Angles are named after its creator W.D. Gann, and the theory is used across the verticals for various set of analysis. Profoundly known for its application in the securities and commodities price feasibility analysis, the intensity, and the logic behind the application of Gann theories across various industrial principles and practices are phenomenal. Gann angle approach is based on x-degree angle detection from the origin or base point used for estimation, wherein important trends are detected.

Applying the concept of Gann, the model proposed in this manuscript is to use the object-based sensors to detect the distance from the primary object to the tracking object, and using the latitude and longitude details of the tracking object (to), the Gann angle degree shall be developed Figure 3.1.

Based on the Gann angle detected, each angle border is coded in a sequential manner, and the motion of the projectile or the object is tracked between one specific angle ranges. Thus, for every "n" period in further the motion of the object is tracked for identifying the possible angle in which the trajectory could be forming. In similar manner, even for the primary object (Po) too, the motion is captured based on the latitude and longitude and the possible projectile of the object is developed [18].

The interception method adapted here is to find the degree of path for both the objects (Po and To) and identify any interception areas between the Gann angles. For instance, if there are three major areas wherein the object crossing each other is identified, it shall be narrowed down as a 'potential interception area' in motion.

The process is repeated for every "n" period, depending on the speed, height or other relative metrics as adapted in the earlier studies. However, such metrics shall be used for deciding the appropriate time frame for measuring the motion analysis. Based on the number of interception layers in the angles forming as diamonds or squares, such areas can be seen as sensitive zone for interception.

Depending on the motion of both the primary and secondary objects, the projectile path interceptions could alter based on the fresh Gann Angles. In the initial Gann Angles, if new interception location is formed, and no over-lapping is formed, such zones shall be removed from the Threat Zone count, and the new ones are added. If there is any over-lapping of the zones to the earlier identified zones, then the classification of possible threat of interception in such a zone shall be upgraded.

By adapting such a system, the scope of analysis in terms of path can be easier and it leads to minimalistic approach in the detection process. For instance, if the speed or the height or traffic or other metrics are used as the primary parameters, there could be huge modifications to such metrics in a real-time environment. Whereas, when the process is based on an angle detection, despite of small fluctuations in the speed or obstructions in the path etc., still the path and feasibility of the movement is broad-lined, and at every "n" period when the analysis is carried out, it refers to the multiple inputs like variance in angles from the origin, and the possible areas wherein the interception can take place.

If the purpose is to find the exact location and time of the trajectory cross is the objective, there are many existing complex solutions. But to identify the potential zone of threat, relying on the Gann Angle approach can lead to sustainable outcome.

**3.2. Rationale of the Approach.** More often the trajectory assessments are carried out for two different aspects. One to understand the intersection points, and the secondary towards predicting the trajectory path, wherein necessary action to thwart any such challenges can take place. However, considering certain metrics like momentum, obstructions, speed, weight, path glide, etc. multiple sets of elements are to be tracked in terms of predicting the trajectory and interceptions, which could increase the complexities of computation [7].

Whereas, in the preliminary level, a simple angle-based assessment of the movement refers to the possible line of movements for the object. For instance, when an object is driving in a direction, the angles at x-degrees are drawn to either direction of movement. Thus, there is a clear path projection as to between what angles the object is heading on. In the following "n" period, when the reassessment of the latitude and longitude is taking place, it refers to the angular shift or continuity taking place. Accordingly, the angles can be extended to the "direction of the movement".

Similarly, when both the objects like the primary object and the tracking objects movement angles are decided, it shall help in mitigating the risks and improving the potential interception areas classification. Adapting to such patterns, can help in reducing the load on different set of metrics being captured, and thus mitigating the complexities pertaining to the process.

**3.3. Primary and Target Object.** The object in the context of the proposed model could be something which is in movement. Irrespective of the direction and the path, speed or other metrics, the object could be presumed for an autonomous vehicle or UAV or even a human driven vehicle etc. The classification in terms of primary and target objects is as follows.

The primary object is the object which is in the control of the monitoring team and being controlled for its maneuvering in a specific direction. On contrary, the target object is the secondary object which is being targeted for understanding the path and projectile. For tracking the target object and the primary target, the need for understanding the latitude and longitude position is paramount. The whole process of analysis shall be based on the latitude and longitude assessment which can be procured based on the GPS trackers [3], [8].

**3.4. GPS Trackers.** A global positioning system, as a tracker, is a device installed on an object, and any positional changes to the object are tracked over a map. Based on real-time tracking, the tracking of factors like latitude and longitude, the direction of movements can easily be tracked for an application system [6].

**3.5. Latitude and Longitude.** Latitude and longitude coordinates are intended for determining and describing the position as well as location of any point on the Earth's surface.

**3.6. Interception Points..** In the motion of an object, there is a certain path in which the object moves depending on the speed, path etc. In the trajectory planned for the process, there could be certain areas wherein two or more objects in its path could be colliding and such points of collision can be seen as interception points. In the context of the proposed model, the interception points shall be formed based on the overlapping Gann points in the angles derived from the directions in which the Gann angles are formed for both the Primary Object and the Target Object [9], [12].

**3.7. "n" Period.** "n" be the notional period represented here wherein n can be a specific period for which the next course of latitude and longitude analysis and the direction of the objects of interest in motion is targeted. Unless the "n" period is computed, identifying the next overlapping intercept points is not feasible. Thus, there is a need for appropriate levels of estimating the n-period angle of movements.

**3.8. Threat Zone Count.** The threat zone count is the summation of a number of squares or block overlaps intercepted with two overlapping zones of Gann Angles related to the primary and target objectives. Depending on the number of additions and eliminations of the overlaps, for each period "n" a new number of threat zone counts shall be imperative for one primary object in motion to the target objects.

In furtherance, the same concept can be applied to multiple object movements too to trace the potential areas of trajectory interceptions, and that can help in addressing the possible movements and path [13].

**3.9. The classification strategy.** The suggested model performs zero-shot learning [19] based on binary classification of trajectory interceptions of the moving objects such that, they are prone to collision or not. Unlike conventional machine learning-based classification strategies, the zero-shot learning approach performs classification without a training phase. However, the zero-shot learning model can perform classification on both seen class as well as unseen class data [20]. The suggested model performs binary classification of the fewer seen class data. Here, the fewer seen class data [21] denotes the combination of seen and unseen class data. The objective function derived to perform the classification of trajectory interceptions is capable to classify the trajectory zones as a safe zone, threat zone found, threat zone with less possibility of collision, threat zone with moderate possibility of collision, and threat zone with the certainty of collision. As a result, based on the classification result, the machine intelligence can alert the driving forces of the moving objects such that:

If the class predicted is a safe zone then no alert to driving forces.

If the class predicted is a threat zone, an alert with no action recommendation to driving forces.

If the class predicted is a threat zone with less collision possibility (yellow zone), then results in a continuous alert about collision scope to driving forces.

If the class predicted is a threat zone with moderate collision possibility (orange zone), then results in a continuous alert of a recommended action (such as slow down the object, or trajectory track change) about collision scope to driving forces.

If the class predicted is a threat zone with high collision possibility (red zone), then results from a continuous alert about collision scope with recommended action (stop the object, if not slow down and change the trajectory tracking of the object).

**3.10. The Data.** The data used in experiments have been synthesized from the compilations of the trajectory interceptions of the moving vehicles captured on cc cameras, which have publicly been available on YouTube [22]. Overall, 1000 images were captured from these compilations. Among these, 215 captures were pruned due to a lack of sensitivity and specificity in trajectory interception observed. The rest of the captures were annotated as having trajectory interceptions prone to collision (positive class), and safe trajectory interceptions (negative class). The count of positive class and negative class captures are 391 and 394 respectively. These resultant captures were preprocessed using OpenCV [23] resulting in GPS coordinates of the sources of moving vehicles. The further phase discovers the further GPS coordinates of the trajectories of the corresponding vehicles. Afterward, determines the Gann-inspired angles for each of the GPS coordinates of the corresponding vehicles. For each capture of both positive and negative classes, a set of records will be framed in the format projected in the following figure (figure 3.2). The projected figure (figure 3.2) indicating the record format of the processed dataset representing the both classes positive and negative such that, for each object $V_i$, represents set of GPS coordinates$[C_1,\ C_2,\ ...,\ C_m]$, and for each coordinate $C_j$discovers set of Gann angles based zones$[GZ_1,\ GZ_2,\ ...,\ GZ_p]$

**3.11. The Objective Function of Collision Prediction.** This section explores the objective function of the proposed binary classification strategy to predict trajectory interceptions with collision scope between two moving objects.

**3.11.1. Model Definition..** In order to predict the scope of trajectory interception between the given two moving objects considered, the key phases involved are projected in the following description. For a given two objects stated as primary object $P$ and target object $T$

Initial step of the suggested model discovers all GPS coordinates $P(L)$,$T(L)$ of the moving directions of the respective objects. Following, for each GPS coordinate of the both objects, discovers GANN angles. Later, the suggested model discovers trajectories of the both objects. Further for each trajectory $P_t$ of the primary object $P$, verifies the scope of interception between the trajectory$P_t$of primary and each trajectory $T_t$ of target

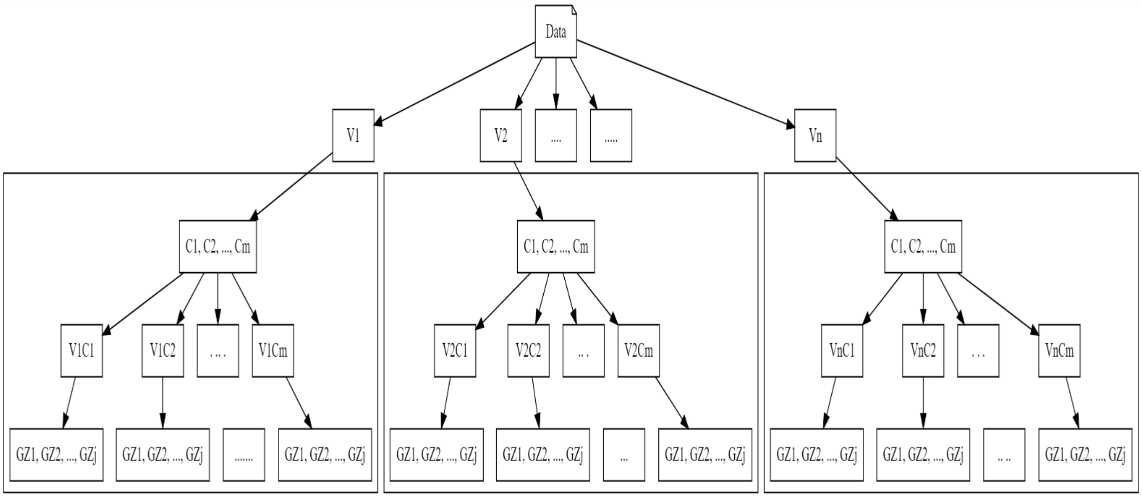


Fig. 3.2: Each capture of both positive and negative classes

object as follows If GPS coordinates of the both objects under the present trajectory of primary and target objects same, then determines, Gann angle based zones indexed in clockwise direction for both primary and secondary objects. If the trajectory of primary object and trajectory of target object are sharing the same index of Gann angle zone, then the respective zone stated as threat zone. If the criteria meets at subsequent GPS coordinate, then threat zone states as threat zone-yellow If criteria meets at further GPS coordinates, then the corresponding threat zone will be stated as threat zone-orange and threat zone-red in respective order.

**3.12. Mathematical Modeling of the Approach.**

1. **Definitions:**
   - $P$ // primary object
   - $T$ // target object
   - $P(L)$ // series of GPS coordinates observed for primary object $P$
   - $T(L)$ // series of GPS coordinates observed for target object $T$, which is as follows:
   - $D$ // total duration of the objects in motion
   - $u$ // the unit of time
2. **GPS Coordinate Tracking:**
   - $i = 1$
   - while $(i \cdot u) \leq D$ //Begin
     - $P(L) \leftarrow \text{GPS}(P)$ // The Eq 1 present GPS coordinates of primary object
     - $T(L) \leftarrow \text{GPS}(T)$ // The Eq 2 present GPS coordinates of target object
     - $i \leftarrow i + 1$
   - End
3. **Gann Angle Series Creation:**
   - For each $g_i \in P(L)$
     - $d^0 = 0°$ // present angle of the Gann series
     - $S°(g_i)$ // series of angles, which is an empty set
     - while $d° < 360°$ Begin
       - $d° \leftarrow d° + x°$
       - $S°(g_i) \leftarrow d°$
     - End
4. **Collision Scope Detection:**
   - Let $aI$ be the angle index that meets the criteria $1 \leq aI \leq |S°(g_i)|$ and representing GANN angles

in clockwise direction. Begin: // Eq 3
  - For each $g_i \in P(L) \cap T(L)$
    * The object's trajectory (Zone Angle of Moving Object) of primary and target objects denoted as primary trajectory $P_t$ and target trajectory $T_t$ referred by the expressions $P_t^{aI}$ and $T_t^{aI}$.
    * if $(aI \notin \text{thrZ} \wedge (P_t^{aI} \cap T_t^{aI}) \neq \emptyset)$ Begin
      · $\text{thrZ} \leftarrow aI$ // Eq 4
    * End
  - Repeat for other conditions and equations as required.
- End: collisionScopeDetection

5. **Additional Steps and Details:**
   - The stated 'collisionScopeDetection' repeats if there is a change in angle Index $aI$.
   - Additional steps and details as required.

**4. Experimental Study Analysis.** This section details the experimental study carried out to assess the performance of the suggested zero-shot learning based binary classification of trajectory interceptions as prone to collision or safe. The 10-fold cross validation was adopted to scale the precision, specificity, sensitivity and accuracy of the suggested classification model. In order to exhibit the performance advantage of the suggested model, the values exhibited for cross validation metrics were compared to the cross validation metric values exhibited by the contemporary model COLLIDE-PRED [17]. The comparative study of the resultant cross validation metric values of the proposed and contemporary models exhibiting that the proposed model PCSMO is outperforming the contemporary model towards prediction of collision scope between moving objects. Python was used to implement the proposed approach [24], and the code was built using the Python editor PyCharm [25]. In this regard, I5-7th gen Intel processor with 32 GB of memory and a 1TB storage was considered for the hardware requirements.

Gann Theory is applied in the PCSMO trajectory detection model. The foundation of the novelty of our model is the Gann Angle, named after W.D. Gann, which is widely applied in commodities and securities price feasibility analysis. These methods are specifically applied to trajectory interception classification in our model, a novel application that has not been explored before. The x-degree angles are the particular parameters that are obtained from Gann Angles and are crucial in identifying movement trends starting from an origin or base point. The application of these angles enables our model to predict interception points by identifying overlapping Gann angles, which are crucial for determining the potential collision zones between the Primary Object and the Target Object. It is necessary to compute intercept points using the 'n' period parameter, which establishes a time frame for trajectory analysis. Without this temporal component, potential overlapping intercept points between moving objects cannot be identified. The significance of this parameter for the temporal analysis of object trajectories led to its selection. Threat Zone Count is another important parameter in the PCSMO algorithm. A quantitative indicator of the potential collision scope is the sum of squares or block overlaps within two overlapping Gann Angle zones. Since this parameter physically represents collision risk areas, we use it to evaluate the PCSMO algorithm in our experimental study. Finally, we conclude that the theoretical significance of our experimental parameters for Gann Theory, their analytical power in other domains, and their empirical significance in trajectory analysis and collision prediction within the PCSMO model, guided their selection. The statistics of the fewer seen class data that detailed in section 3.10 are exhibited in following table (table 4.1).

The ratio of true positive predictions to made positive predictions is known as precision, or positive predictive value. This metric is critical when the cost of false positives is high. In terms of accurate collision scenario prediction without overprediction, the PCSMO model performed better than COLLIDE-PRED.

The precision of the cross-validation measure relates to the positive predictive value acquired by cross-validation from both the proposed PCSMO and existing COLLIDE-PRED methods, respectively. Figure 4.1 depicts the precision data obtained from each cross-validation fold. The positive predictive value (PPV) acquired by the proposed PCSMO method is larger than that obtained by COLLIDE-PRED, implying that the proposed method can effectively reduce false negative rates. In comparison to the current model, COLLIDE-PRED, the metric precision values obtained show the relevance of the PCSMO with low variance.PCSMO shows a higher

Table 4.1: The statistics of the fewer seen class data

| Parameter | Count |
|---|---|
| No of captures from source compilations | 1000 |
| No of captures considered for fewer seen class data preparation | 785 |
| No of captures listed as positive class (trajectory interceptions prone to collision) | 391 |
| No of captures listed as negative class (safe trajectory interceptions) | 394 |
| No of positive class records | 3152 |
| No of negative class records | 3519 |
| No of unseen records | 672 |

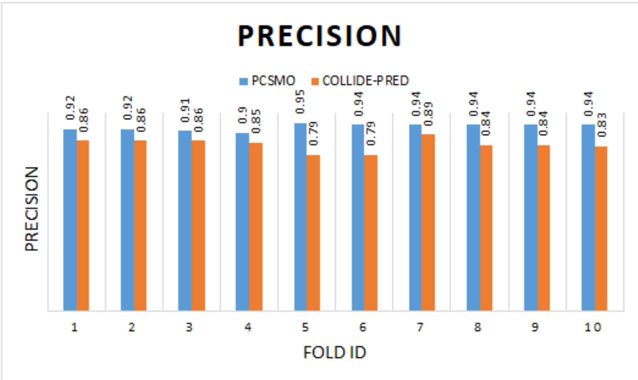


Fig. 4.1: The positive predictive values observed from cross-validation

mean precision (0.930) compared to COLLIDE-PRED (0.841). This indicates that PCSMO is more reliable in its positive predictions, with fewer false positives on average.

The percentage of real negatives that are correctly identified is known as the True Negative Rate, or Specificity. This displays the accuracy of the model's non-collision detection. Indicating PCSMO's dependability in locating safe trajectories, it showed high specificity and low variance.

The True Negative Rate, which corresponds to the specificity of the PCSMO and COLLIDE-PRED techniques, is the result of tenfold cross-validation. Figure 4.2 summarizes the specificity acquired from each of the 10-folds of the cross-validation. The numbers obtained for metric specificity indicate the relevance of the PCSMO with minimum variation from the current model, COLLIDE-PRED. PCSMO has a higher mean specificity (0.927) than COLLIDE-PRED (0.837), suggesting that PCSMO is better at correctly identifying negative cases without falsely categorizing them as positive.

They are balanced by the F-Measure, which is the harmonic mean of recall (sensitivity) and precision. Particularly helpful in cases of unequal class distribution. Indicating a balanced performance between sensitivity and precision, the f-measure of the PCSMO model was significantly higher than COLLIDE-PRED.

For the recommended and contemporaneous models, the cross-validation metric "F-measure" was determined among 10 folds, as shown in Figure 4.3. In descending order, the average f-measures for PCSMO and COLLIDE-PRED are displayed. The comprehensive statistics of the F-measure generated from tenfold cross-validation are shown in Figure 4.3. The metric f-measure values obtained demonstrate that the PCSMO is more relevant than the current model COLLIDE-PRED in terms of performance. The proposed model PCSMO outperforms the present model COLLIDE-PRED, as evidenced by the substantial F-measure value produced from the recommended model PCSMO. The mean F-measure for PCSMO (0.927) exceeds COLLIDE-PRED's (0.839), which suggests a better balance between precision and sensitivity in PCSMO, making it a more robust model overall. The ability of the model to recognize every positive instance is known as its sensitivity, or true

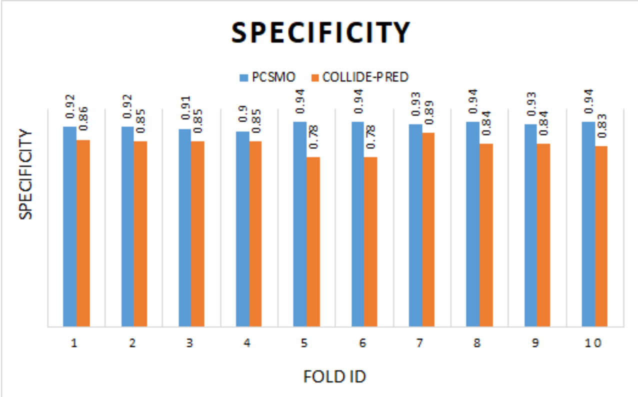


Fig. 4.2: The True Negative Rate obtained from cross-validation

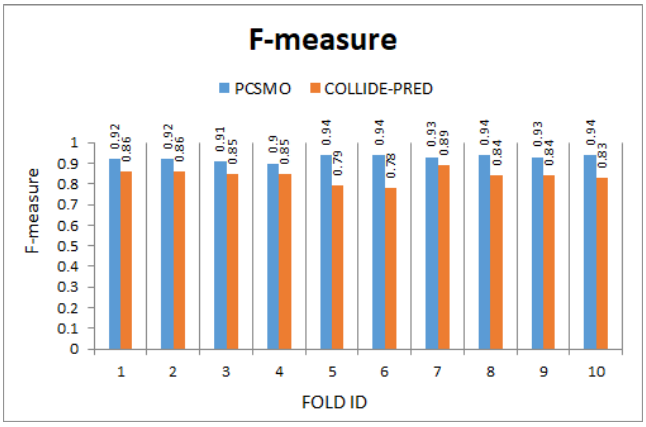


Fig. 4.3: The f-measure observations from tenfold cross-validation

positive rate. The PCSMO model demonstrated exceptional sensitivity in locating possible collision points across the majority of folds, despite having a lower true positive rate.

The true positive rate also refers to the sensitivity discovered by cross-validation on both PCSMO and COLLIDE-PRED techniques, respectively. Figure 4.4 depicts the fold level sensitivity in further detail. When comparing the PCSMO to the current model COLLIDE-PRED, the metric sensitivity values show that the PCSMO outperforms the COLLIDE-PRED. Despite having a lower true positive rate, the suggested PCSMO model appears to have superior sensitivity in the majority of folds. PCSMO's mean sensitivity (0.949) is greater than that of COLLIDE-PRED (0.874). PCSMO is more effective at correctly identifying true positive cases, indicating a lower miss rate for actual positives. The percentage of records correctly classified is called accuracy. It is a crucial performance metric for models in classification problems. The PCSMO model predicted collision and non-collision scenarios more accurately than the COLLIDE-PRED model in the majority of cross-validation folds.

The "accuracy" is a cross-validation statistic that measures the proportion of properly categorized records to the total number of records. PCSMO and COLLIDE-PRED both have good overall prediction accuracy. Figure 4.5 shows the accuracy statistics derived from tenfold cross-validation in more detail. When comparing the PCSMO to the current model COLLIDE-PRED, the metric accuracy results show that the PCSMO outperforms the COLLIDE-PRED. The accuracy distribution chart for cross-validation of the PCSMO as well as COLLIDE-PRED models is shown in Figure 4.5. The mean accuracy of PCSMO (0.939) is significantly higher than that

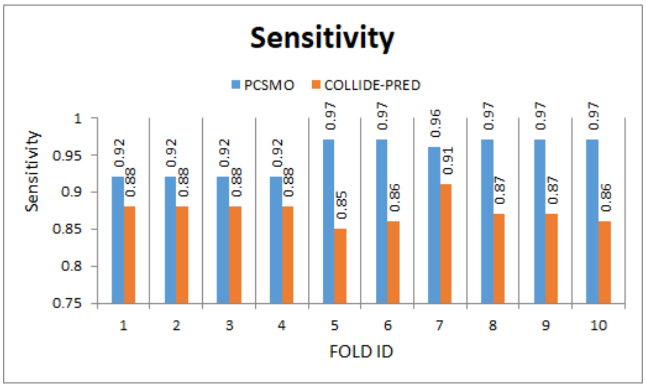


Fig. 4.4: The sensitivity observed from tenfold cross-validation

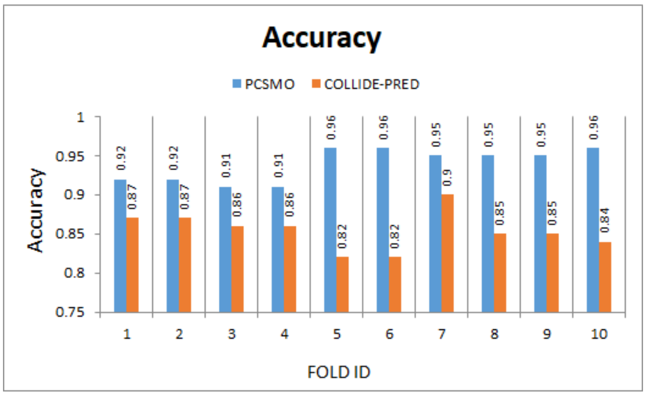


Fig. 4.5: Accuracy obtained from tenfold cross-validation

of COLLIDE-PRED (0.854), meaning that PCSMO correctly predicts both positive and negative outcomes more often than COLLIDE-PRED. In binary classification problems, the Matthews Correlation Coefficient (MCC) provides more information than accuracy when classes have significant differences in size. It evaluates negatives and true versus false positives and is thought to be balanced. PCSMO's MCC values exceeded COLLIDE-PRED's, demonstrating the predictive ability of the model.

The cross-validation metric MCC has been measured over the proposed and contemporary models among ten folds, as shown in Figure 4.6. The MCC observed for PCSMO and COLLIDE-PRED in the respective order. The detailed statistics of MCC obtained from tenfold cross-validation have been explored in Figure 4.6. The values obtained for metric MCC exhibits the significance of the PCSMO with better performance while compared to the contemporary model COLLIDE-PRED. PCSMO's mean MCC (0.875) is notably higher than COLLIDE-PRED's (0.714). Since MCC is a balanced measure even when the classes are of different sizes, a higher MCC indicates a better performance of PCSMO, with a stronger correlation between observed and predicted classifications.

**5. Conclusion.** In conclusion, it can be challenging to evaluate trajectories and locate intersections where moving objects might collide, particularly in road transportation where cars can travel in several directions. Potential collision zones between moving objects are predicted by Zero-shot Learning-based Trajectory Interception Classification. The potential collision locations and parameters between the primary and target objects are determined using angle-based analysis, which is incorporated into our PCSMO model. Threat zones are defined by overlapping Gann angles. After a thorough 10-fold cross-validation, the model's efficacy was determined.

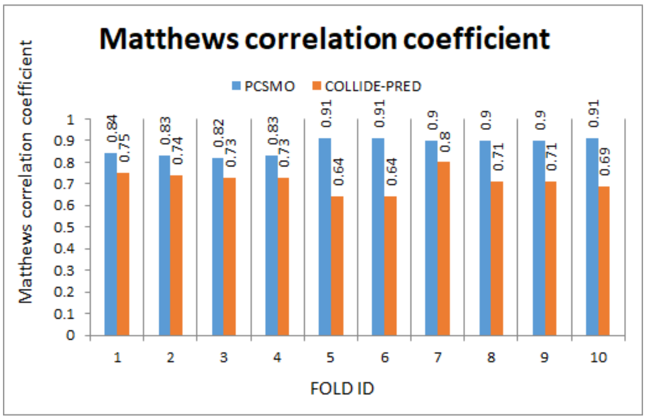


Fig. 4.6: The Mathews Correlation Coefficient (MCC) observed from the tenfold cross-validation

It fared significantly better than the COLLIDE-PRED model in every performance metric, with a prediction accuracy above 90%. From wide to narrow, the PCSMO model identifies the angle range and width of potential collision zones. The micro-level collision point is not precisely located by it. The Gann Nine scale approach will be added to this model in order to improve collision scope predictions. By using this refined scale, we hope to more accurately define the threat range and provide a second-level analysis that could significantly lower the risk of collisions. By defining threat zones, the Gann Nine square model extension will help us focus our predictive skills.

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# TRAJECTORY INTERCEPTION CLASSIFICATION FOR PREDICTION OF COLLISION SCOPE BETWEEN MOVING OBJECTS

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**Abstract.** In the fields of autonomous navigation and vehicle safety, accurately predicting potential collision field points between moving objects is a significant challenge. A novel computing technique to enhance trajectory interception analysis is presented in this paper. Our objective is to develop a field model that can accurately forecast collision zones, improving road transportation safety and the use of autonomous cars. Our main contribution is a binary classification model called PCSMO (Prediction of Collision Scope between Moving Objects), which is based on zero-shot learning. Gann angles, which are typically 45 degrees, are used to analyze the trajectories of moving objects. This method is inspired by GANN (Gann Angle Numeric Nomenclature). Compared to earlier techniques, this model more accurately identifies potential collision collision interception zones. The technique computes Gann angles for trajectory analysis and extracts GPS coordinates of moving objects from video data using OpenCV. It offers a more sophisticated comprehension of object movement patterns and points of interception. To assess the precision, recall, F1-score, and prediction accuracy of our model, we employ 10-fold cross-validation. Comparing the PCSMO model to existing models, these metrics demonstrate how well the PCSMO model predicts potential collision zones. Our approach, we discovered, enhances trajectory analysis—a critical component of safer autonomous navigation systems. With potential applications in autonomous vehicle and UAV safety, the PCSMO model improves field interception classification.

**Key words:** Collision, Moving Objects. Global Positioning System, Machine Learning, Binary Classification, Gann Angle Degree, Trajectory Interception Detection, Unmanned Aerial Vehicles, Zero-Shot Learning.

**1. Introduction.** A conglomeration of advanced technological systems in combination with contemporary mobility solutions has created a paradigm shift in the ways supply chain ecosystem, and commutation systems across the world are becoming safer. There is a various set of tools, technical, management practices, and instrumentation engineering practices that are paving for safety in the mobility systems. Right from a two-wheeler to the jumbo-jet airliners at every level, the reliance on technology solutions has raised notches, and today, there are scores of control models that guard safe transportation and mobility.

Today, the contemporary practices of Unmanned Aerial Vehicles (UAVs), self-driven cars, drone-based delivery chains, robotic solutions, and AI solutions manning the traffic monitoring and control systems refer to a paradigm shift in futuristic solutions. While the scope of new-age solutions looks promising, still the scope for enhancements to the security and overall efficiency of autonomous vehicles is imperative [1].

Increasing demand for autonomous vehicles and vehicles with sensors for traffic mobility is on the rise, the systems must be more equipped in terms of mechanisms, patterns in which the systems are being deployed, and the measures that can help in improving the overall process of drive-safe conditions. In addition to the road-safety conditions with driver-less vehicles, even in the case the unmanned aerial vehicles, the role of systems in predicting the projectile path and the possible cross in the trajectory is impeccable need. As the domain is gaining traction, and the need for more comprehensive solutions are imperative, in this manuscript, the scope of developing prediction models that can be resourceful in the trajectory path crossing conditions is explored.

Projectile path trajectories estimation models are significant in the domain, and there are numerous models that were developed which could address the patterns and possible intersections. One key area wherein the studies are limited is the scope of motion analysis pertaining to a greater number of projectiles being in its motion simultaneously. However, there are a certain set of fundamental mathematical models and physics-theories-related equations and algorithms proposed earlier, which can address the projectile path conditions

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[2], [3]. Developing a secondary system that can create affirmative to the primary analysis approach can be a significant solution and embracing such solutions can lead to significant benefits for the predictive models, which can be resourceful in autonomous vehicles or UAV movement too. In this manuscript, focus is on the scope of continuous objective movement tracking and estimation of any close areas wherein the potential trajectory cross, and early stage of predictions of such trajectories [4]. Following are the key objectives considered in development of the proposed model:

- The first objective is to track the projectile path of an object in motion and its trajectory
- The second objective is to understand how the projectile path of an object can interfere with the other object in motion that is being tracked.
- Classification of the possible interceptions according to threat levels is based on the dynamic movement of the projectiles.

Targeting the above objectives, the approach in the model is to develop a systematic model wherein the key paths used by the projectiles are monitored and accordingly develop an interception mapping system that can change according to the real-time environment.

**2. Related Work.** Scores of models pertaining to object collisions on path prediction, accidents-related risk mitigation in autonomous vehicle segments, traffic density-based accident prediction zones, potential paths of gliding, and intersections are some of the actual ranges of studies explored in the literature review. From the summation of key points in the literature, the following are some of the critical observations and learnings: The majority of the trajectory-related studies or safety-related studies are reliant on third-party components or tools like sensors, GPS positioning tools, density meters, altitude meters, speedometers, etc. The performance of the whole system is dependent on the inputs attained from the equipment or tools adapted in the models. Irrespective of the efficacy of the models, any depletion in the quality of the tools used for gauging metrics could be a serious threat in terms of miscalculation and ineffective predictions of the intersections [5–11].

The other key observation is about application of the solutions for univariate analysis, like one moving object movement compared to the other static object sensors, etc. When there are more than one object making moves in zigzag or varying directions, the complexities of accuracy are high for the predictive models [12–16].

"COLLIDE-PRED," developed by Author et al. [17], uses the motion of objects moving to provide collision predictions. It is a pipeline that begins with object identification, which is utilized for object tracking; afterwards, trajectory prediction is conducted, which culminates in collision detection. The authors indicated that the COLLIDE-PRED will determine the probable site of the collision. This model attempted to determine the target object's trajectory's collision scope, which often exhibits false alarm. In addition, the collision scope of moving objects can only be predicted using this approach for offline video streams.

Applying the machine learning model is seen as a promising solution from the literature towards testing the label classification approach and other such metrics, which are significant for the execution of the models. There are scales of statistical and technology-centric models discussed in the literature towards understanding the scope of autonomous vehicle safety in its trajectory. However, there is a need for more explorative studies in the domain to improve the overall efficiency with which the solutions can be managed. In order to address the constraints addressed in this review of contemporary literature, this manuscript suggests a novel zero-shot binary classification model that discovers threat zones and safe zones of trajectory interceptions.

In the further sections of this manuscript, Section 2 refers to the related work summary from the literature review. Section 3 provides insights into the materials and methods, the proposed model narrative, its algorithm flow, and other key metrics that signify the mode. Section 4 provides insights into the experimental study, and Section 5 refers to the conclusion based on the efficiency aspects estimated from the model.

**3. Proposed Method and Materials.** The method of classifying trajectory interceptions with and without collision scope between moving objects and respective materials have been explored in this section. The section includes the narrative of the suggested model. By uniquely combining zero-shot learning with GANN principles, the PCSMO (Prediction of Collision Scope between Moving Objects) predictive model presents a novel approach to collision detection. Unlike traditional models, the PCSMO model can reliably predict collision points without historical data thanks to this integration. The key to this innovation is the application of Gann angles, which are used in financial markets, to trajectory analysis. These angles provide a new perspective

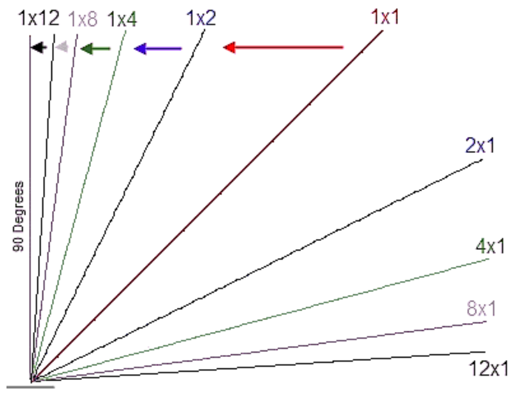


Fig. 3.1: The Gann angle degree

on trajectory interception classification by enabling the PCSMO model to predict collision points in dynamic scenarios such as road traffic and autonomous vehicle navigation. In order to improve Gann angle calculations, the model additionally makes use of OpenCV to extract precise GPS coordinates from video data. This approach adds something uniquely to the field of trajectory analysis while improving the predictive power of the model.

**3.1. Model Narrative.** The model proposed in this manuscript is based on the trajectory detection requirements, and fundamentally the concept of Gann Theory is used in the development of the model. While the metrics and techniques used in the assessment of the path and motion are prevalent in many of the earlier studies, application of GANN angle formations is a unique concept explored in this manuscript.

Gann Angles are named after its creator W.D. Gann, and the theory is used across the verticals for various set of analysis. Profoundly known for its application in the securities and commodities price feasibility analysis, the intensity, and the logic behind the application of Gann theories across various industrial principles and practices are phenomenal. Gann angle approach is based on x-degree angle detection from the origin or base point used for estimation, wherein important trends are detected.

Applying the concept of Gann, the model proposed in this manuscript is to use the object-based sensors to detect the distance from the primary object to the tracking object, and using the latitude and longitude details of the tracking object (to), the Gann angle degree shall be developed Figure 3.1.

Based on the Gann angle detected, each angle border is coded in a sequential manner, and the motion of the projectile or the object is tracked between one specific angle ranges. Thus, for every "n" period in further the motion of the object is tracked for identifying the possible angle in which the trajectory could be forming. In similar manner, even for the primary object (Po) too, the motion is captured based on the latitude and longitude and the possible projectile of the object is developed [18].

The interception method adapted here is to find the degree of path for both the objects (Po and To) and identify any interception areas between the Gann angles. For instance, if there are three major areas wherein the object crossing each other is identified, it shall be narrowed down as a 'potential interception area' in motion.

The process is repeated for every "n" period, depending on the speed, height or other relative metrics as adapted in the earlier studies. However, such metrics shall be used for deciding the appropriate time frame for measuring the motion analysis. Based on the number of interception layers in the angles forming as diamonds or squares, such areas can be seen as sensitive zone for interception.

Depending on the motion of both the primary and secondary objects, the projectile path interceptions could alter based on the fresh Gann Angles. In the initial Gann Angles, if new interception location is formed, and no over-lapping is formed, such zones shall be removed from the Threat Zone count, and the new ones are added. If there is any over-lapping of the zones to the earlier identified zones, then the classification of possible threat of interception in such a zone shall be upgraded.

By adapting such a system, the scope of analysis in terms of path can be easier and it leads to minimalistic approach in the detection process. For instance, if the speed or the height or traffic or other metrics are used as the primary parameters, there could be huge modifications to such metrics in a real-time environment. Whereas, when the process is based on an angle detection, despite of small fluctuations in the speed or obstructions in the path etc., still the path and feasibility of the movement is broad-lined, and at every "n" period when the analysis is carried out, it refers to the multiple inputs like variance in angles from the origin, and the possible areas wherein the interception can take place.

If the purpose is to find the exact location and time of the trajectory cross is the objective, there are many existing complex solutions. But to identify the potential zone of threat, relying on the Gann Angle approach can lead to sustainable outcome.

**3.2. Rationale of the Approach.** More often the trajectory assessments are carried out for two different aspects. One to understand the intersection points, and the secondary towards predicting the trajectory path, wherein necessary action to thwart any such challenges can take place. However, considering certain metrics like momentum, obstructions, speed, weight, path glide, etc. multiple sets of elements are to be tracked in terms of predicting the trajectory and interceptions, which could increase the complexities of computation [7].

Whereas, in the preliminary level, a simple angle-based assessment of the movement refers to the possible line of movements for the object. For instance, when an object is driving in a direction, the angles at x-degrees are drawn to either direction of movement. Thus, there is a clear path projection as to between what angles the object is heading on. In the following "n" period, when the reassessment of the latitude and longitude is taking place, it refers to the angular shift or continuity taking place. Accordingly, the angles can be extended to the "direction of the movement".

Similarly, when both the objects like the primary object and the tracking objects movement angles are decided, it shall help in mitigating the risks and improving the potential interception areas classification. Adapting to such patterns, can help in reducing the load on different set of metrics being captured, and thus mitigating the complexities pertaining to the process.

**3.3. Primary and Target Object.** The object in the context of the proposed model could be something which is in movement. Irrespective of the direction and the path, speed or other metrics, the object could be presumed for an autonomous vehicle or UAV or even a human driven vehicle etc. The classification in terms of primary and target objects is as follows.

The primary object is the object which is in the control of the monitoring team and being controlled for its maneuvering in a specific direction. On contrary, the target object is the secondary object which is being targeted for understanding the path and projectile. For tracking the target object and the primary target, the need for understanding the latitude and longitude position is paramount. The whole process of analysis shall be based on the latitude and longitude assessment which can be procured based on the GPS trackers [3], [8].

**3.4. GPS Trackers.** A global positioning system, as a tracker, is a device installed on an object, and any positional changes to the object are tracked over a map. Based on real-time tracking, the tracking of factors like latitude and longitude, the direction of movements can easily be tracked for an application system [6].

**3.5. Latitude and Longitude.** Latitude and longitude coordinates are intended for determining and describing the position as well as location of any point on the Earth's surface.

**3.6. Interception Points..** In the motion of an object, there is a certain path in which the object moves depending on the speed, path etc. In the trajectory planned for the process, there could be certain areas wherein two or more objects in its path could be colliding and such points of collision can be seen as interception points. In the context of the proposed model, the interception points shall be formed based on the overlapping Gann points in the angles derived from the directions in which the Gann angles are formed for both the Primary Object and the Target Object [9], [12].

**3.7. "n" Period.** "n" be the notional period represented here wherein n can be a specific period for which the next course of latitude and longitude analysis and the direction of the objects of interest in motion is targeted. Unless the "n" period is computed, identifying the next overlapping intercept points is not feasible. Thus, there is a need for appropriate levels of estimating the n-period angle of movements.

**3.8. Threat Zone Count.** The threat zone count is the summation of a number of squares or block overlaps intercepted with two overlapping zones of Gann Angles related to the primary and target objectives. Depending on the number of additions and eliminations of the overlaps, for each period "n" a new number of threat zone counts shall be imperative for one primary object in motion to the target objects.

In furtherance, the same concept can be applied to multiple object movements too to trace the potential areas of trajectory interceptions, and that can help in addressing the possible movements and path [13].

**3.9. The classification strategy.** The suggested model performs zero-shot learning [19] based on binary classification of trajectory interceptions of the moving objects such that, they are prone to collision or not. Unlike conventional machine learning-based classification strategies, the zero-shot learning approach performs classification without a training phase. However, the zero-shot learning model can perform classification on both seen class as well as unseen class data [20]. The suggested model performs binary classification of the fewer seen class data. Here, the fewer seen class data [21] denotes the combination of seen and unseen class data. The objective function derived to perform the classification of trajectory interceptions is capable to classify the trajectory zones as a safe zone, threat zone found, threat zone with less possibility of collision, threat zone with moderate possibility of collision, and threat zone with the certainty of collision. As a result, based on the classification result, the machine intelligence can alert the driving forces of the moving objects such that:

If the class predicted is a safe zone then no alert to driving forces.

If the class predicted is a threat zone, an alert with no action recommendation to driving forces.

If the class predicted is a threat zone with less collision possibility (yellow zone), then results in a continuous alert about collision scope to driving forces.

If the class predicted is a threat zone with moderate collision possibility (orange zone), then results in a continuous alert of a recommended action (such as slow down the object, or trajectory track change) about collision scope to driving forces.

If the class predicted is a threat zone with high collision possibility (red zone), then results from a continuous alert about collision scope with recommended action (stop the object, if not slow down and change the trajectory tracking of the object).

**3.10. The Data.** The data used in experiments have been synthesized from the compilations of the trajectory interceptions of the moving vehicles captured on cc cameras, which have publicly been available on YouTube [22]. Overall, 1000 images were captured from these compilations. Among these, 215 captures were pruned due to a lack of sensitivity and specificity in trajectory interception observed. The rest of the captures were annotated as having trajectory interceptions prone to collision (positive class), and safe trajectory interceptions (negative class). The count of positive class and negative class captures are 391 and 394 respectively. These resultant captures were preprocessed using OpenCV [23] resulting in GPS coordinates of the sources of moving vehicles. The further phase discovers the further GPS coordinates of the trajectories of the corresponding vehicles. Afterward, determines the Gann-inspired angles for each of the GPS coordinates of the corresponding vehicles. For each capture of both positive and negative classes, a set of records will be framed in the format projected in the following figure (figure 3.2). The projected figure (figure 3.2) indicating the record format of the processed dataset representing the both classes positive and negative such that, for each object $V_i$, represents set of GPS coordinates$[C_1,\ C_2,\ ...,\ C_m]$, and for each coordinate $C_j$discovers set of Gann angles based zones$[GZ_1,\ GZ_2,\ ...,\ GZ_p]$

**3.11. The Objective Function of Collision Prediction.** This section explores the objective function of the proposed binary classification strategy to predict trajectory interceptions with collision scope between two moving objects.

**3.11.1. Model Definition..** In order to predict the scope of trajectory interception between the given two moving objects considered, the key phases involved are projected in the following description. For a given two objects stated as primary object $P$ and target object $T$

Initial step of the suggested model discovers all GPS coordinates $P(L)$,$T(L)$ of the moving directions of the respective objects. Following, for each GPS coordinate of the both objects, discovers GANN angles. Later, the suggested model discovers trajectories of the both objects. Further for each trajectory $P_t$ of the primary object $P$, verifies the scope of interception between the trajectory$P_t$of primary and each trajectory $T_t$ of target

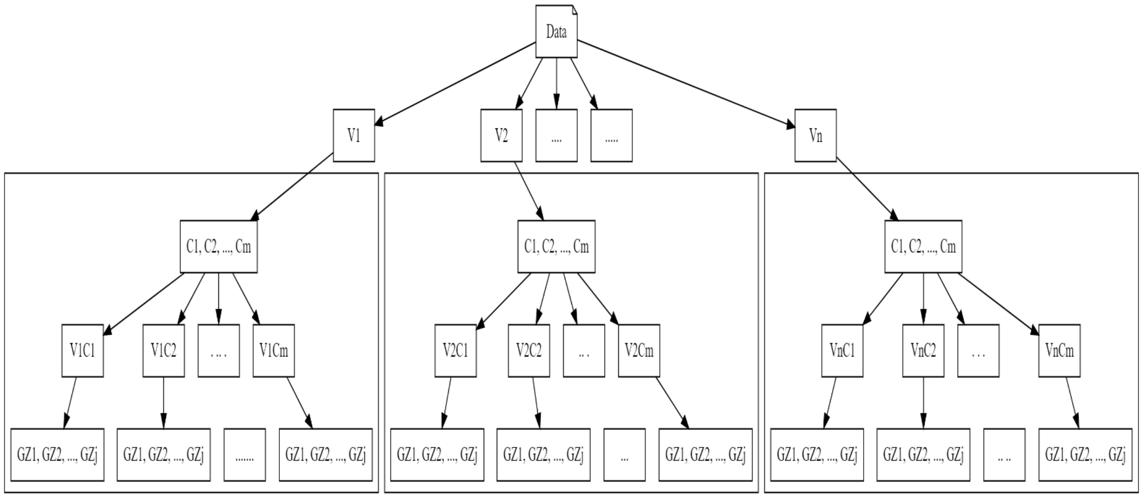


Fig. 3.2: Each capture of both positive and negative classes

object as follows If GPS coordinates of the both objects under the present trajectory of primary and target objects same, then determines, Gann angle based zones indexed in clockwise direction for both primary and secondary objects. If the trajectory of primary object and trajectory of target object are sharing the same index of Gann angle zone, then the respective zone stated as threat zone. If the criteria meets at subsequent GPS coordinate, then threat zone states as threat zone-yellow If criteria meets at further GPS coordinates, then the corresponding threat zone will be stated as threat zone-orange and threat zone-red in respective order.

**3.12. Mathematical Modeling of the Approach.**

1. **Definitions:**
    - $P$ // primary object
    - $T$ // target object
    - $P(L)$ // series of GPS coordinates observed for primary object $P$
    - $T(L)$ // series of GPS coordinates observed for target object $T$, which is as follows:
    - $D$ // total duration of the objects in motion
    - $u$ // the unit of time
2. **GPS Coordinate Tracking:**
    - $i = 1$
    - while $(i \cdot u) \leq D$ //Begin
        - $P(L) \leftarrow \text{GPS}(P)$ // The Eq 1 present GPS coordinates of primary object
        - $T(L) \leftarrow \text{GPS}(T)$ // The Eq 2 present GPS coordinates of target object
        - $i \leftarrow i + 1$
    - End
3. **Gann Angle Series Creation:**
    - For each $g_i \in P(L)$
        - $d^0 = 0^\circ$ // present angle of the Gann series
        - $S^\circ(g_i)$ // series of angles, which is an empty set
        - while $d^\circ < 360^\circ$ Begin
            * $d^\circ \leftarrow d^\circ + x^\circ$
            * $S^\circ(g_i) \leftarrow d^\circ$
        - End
4. **Collision Scope Detection:**
    - Let $aI$ be the angle index that meets the criteria $1 \leq aI \leq |S^\circ(g_i)|$ and representing GANN angles

in clockwise direction. Begin: // Eq 3
  - For each $g_i \in P(L) \cap T(L)$
    * The object's trajectory (Zone Angle of Moving Object) of primary and target objects denoted as primary trajectory $P_t$ and target trajectory $T_t$ referred by the expressions $P_t^{aI}$ and $T_t^{aI}$.
    * if $(aI \notin \text{thrZ} \wedge (P_t^{aI} \cap T_t^{aI}) \neq \emptyset)$ Begin
      · $\text{thrZ} \leftarrow aI$ // Eq 4
    * End
  - Repeat for other conditions and equations as required.
- End: collisionScopeDetection

5. **Additional Steps and Details:**
   - The stated 'collisionScopeDetection' repeats if there is a change in angle Index $aI$.
   - Additional steps and details as required.

**4. Experimental Study Analysis.** This section details the experimental study carried out to assess the performance of the suggested zero-shot learning based binary classification of trajectory interceptions as prone to collision or safe. The 10-fold cross validation was adopted to scale the precision, specificity, sensitivity and accuracy of the suggested classification model. In order to exhibit the performance advantage of the suggested model, the values exhibited for cross validation metrics were compared to the cross validation metric values exhibited by the contemporary model COLLIDE-PRED [17]. The comparative study of the resultant cross validation metric values of the proposed and contemporary models exhibiting that the proposed model PCSMO is outperforming the contemporary model towards prediction of collision scope between moving objects. Python was used to implement the proposed approach [24], and the code was built using the Python editor PyCharm [25]. In this regard, I5-7th gen Intel processor with 32 GB of memory and a 1TB storage was considered for the hardware requirements.

Gann Theory is applied in the PCSMO trajectory detection model. The foundation of the novelty of our model is the Gann Angle, named after W.D. Gann, which is widely applied in commodities and securities price feasibility analysis. These methods are specifically applied to trajectory interception classification in our model, a novel application that has not been explored before. The x-degree angles are the particular parameters that are obtained from Gann Angles and are crucial in identifying movement trends starting from an origin or base point. The application of these angles enables our model to predict interception points by identifying overlapping Gann angles, which are crucial for determining the potential collision zones between the Primary Object and the Target Object. It is necessary to compute intercept points using the 'n' period parameter, which establishes a time frame for trajectory analysis. Without this temporal component, potential overlapping intercept points between moving objects cannot be identified. The significance of this parameter for the temporal analysis of object trajectories led to its selection. Threat Zone Count is another important parameter in the PCSMO algorithm. A quantitative indicator of the potential collision scope is the sum of squares or block overlaps within two overlapping Gann Angle zones. Since this parameter physically represents collision risk areas, we use it to evaluate the PCSMO algorithm in our experimental study. Finally, we conclude that the theoretical significance of our experimental parameters for Gann Theory, their analytical power in other domains, and their empirical significance in trajectory analysis and collision prediction within the PCSMO model, guided their selection. The statistics of the fewer seen class data that detailed in section 3.10 are exhibited in following table (table 4.1).

The ratio of true positive predictions to made positive predictions is known as precision, or positive predictive value. This metric is critical when the cost of false positives is high. In terms of accurate collision scenario prediction without overprediction, the PCSMO model performed better than COLLIDE-PRED.

The precision of the cross-validation measure relates to the positive predictive value acquired by cross-validation from both the proposed PCSMO and existing COLLIDE-PRED methods, respectively. Figure 4.1 depicts the precision data obtained from each cross-validation fold. The positive predictive value (PPV) acquired by the proposed PCSMO method is larger than that obtained by COLLIDE-PRED, implying that the proposed method can effectively reduce false negative rates. In comparison to the current model, COLLIDE-PRED, the metric precision values obtained show the relevance of the PCSMO with low variance.PCSMO shows a higher

Table 4.1: The statistics of the fewer seen class data

| **Parameter** | **Count** |
|---|---|
| No of captures from source compilations | 1000 |
| No of captures considered for fewer seen class data preparation | 785 |
| No of captures listed as positive class (trajectory interceptions prone to collision) | 391 |
| No of captures listed as negative class (safe trajectory interceptions) | 394 |
| No of positive class records | 3152 |
| No of negative class records | 3519 |
| No of unseen records | 672 |

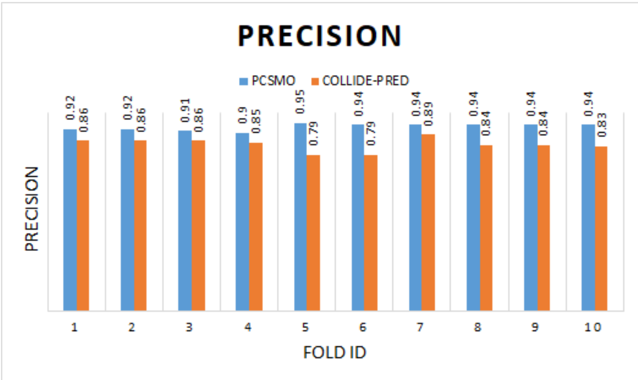


Fig. 4.1: The positive predictive values observed from cross-validation

mean precision (0.930) compared to COLLIDE-PRED (0.841). This indicates that PCSMO is more reliable in its positive predictions, with fewer false positives on average.

The percentage of real negatives that are correctly identified is known as the True Negative Rate, or Specificity. This displays the accuracy of the model's non-collision detection. Indicating PCSMO's dependability in locating safe trajectories, it showed high specificity and low variance.

The True Negative Rate, which corresponds to the specificity of the PCSMO and COLLIDE-PRED techniques, is the result of tenfold cross-validation. Figure 4.2 summarizes the specificity acquired from each of the 10-folds of the cross-validation. The numbers obtained for metric specificity indicate the relevance of the PCSMO with minimum variation from the current model, COLLIDE-PRED. PCSMO has a higher mean specificity (0.927) than COLLIDE-PRED (0.837), suggesting that PCSMO is better at correctly identifying negative cases without falsely categorizing them as positive.

They are balanced by the F-Measure, which is the harmonic mean of recall (sensitivity) and precision. Particularly helpful in cases of unequal class distribution. Indicating a balanced performance between sensitivity and precision, the f-measure of the PCSMO model was significantly higher than COLLIDE-PRED.

For the recommended and contemporaneous models, the cross-validation metric "F-measure" was determined among 10 folds, as shown in Figure 4.3. In descending order, the average f-measures for PCSMO and COLLIDE-PRED are displayed. The comprehensive statistics of the F-measure generated from tenfold cross-validation are shown in Figure 4.3. The metric f-measure values obtained demonstrate that the PCSMO is more relevant than the current model COLLIDE-PRED in terms of performance. The proposed model PCSMO outperforms the present model COLLIDE-PRED, as evidenced by the substantial F-measure value produced from the recommended model PCSMO. The mean F-measure for PCSMO (0.927) exceeds COLLIDE-PRED's (0.839), which suggests a better balance between precision and sensitivity in PCSMO, making it a more robust model overall. The ability of the model to recognize every positive instance is known as its sensitivity, or true

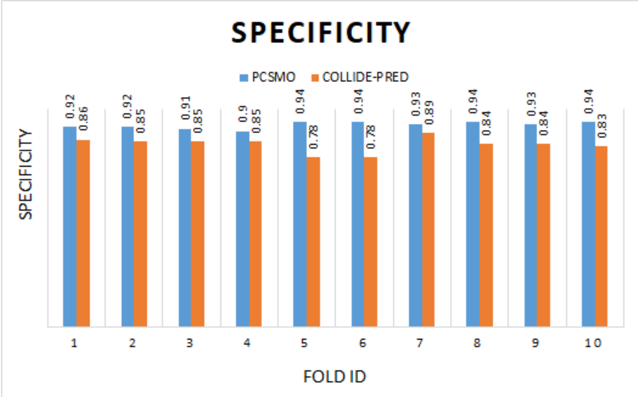


Fig. 4.2: The True Negative Rate obtained from cross-validation

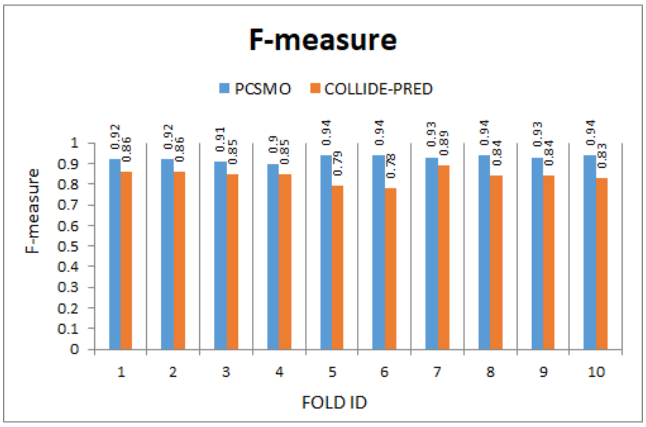


Fig. 4.3: The f-measure observations from tenfold cross-validation

positive rate. The PCSMO model demonstrated exceptional sensitivity in locating possible collision points across the majority of folds, despite having a lower true positive rate.

The true positive rate also refers to the sensitivity discovered by cross-validation on both PCSMO and COLLIDE-PRED techniques, respectively. Figure 4.4 depicts the fold level sensitivity in further detail. When comparing the PCSMO to the current model COLLIDE-PRED, the metric sensitivity values show that the PCSMO outperforms the COLLIDE-PRED. Despite having a lower true positive rate, the suggested PCSMO model appears to have superior sensitivity in the majority of folds. PCSMO's mean sensitivity (0.949) is greater than that of COLLIDE-PRED (0.874). PCSMO is more effective at correctly identifying true positive cases, indicating a lower miss rate for actual positives. The percentage of records correctly classified is called accuracy. It is a crucial performance metric for models in classification problems. The PCSMO model predicted collision and non-collision scenarios more accurately than the COLLIDE-PRED model in the majority of cross-validation folds.

The "accuracy" is a cross-validation statistic that measures the proportion of properly categorized records to the total number of records. PCSMO and COLLIDE-PRED both have good overall prediction accuracy. Figure 4.5 shows the accuracy statistics derived from tenfold cross-validation in more detail. When comparing the PCSMO to the current model COLLIDE-PRED, the metric accuracy results show that the PCSMO outperforms the COLLIDE-PRED. The accuracy distribution chart for cross-validation of the PCSMO as well as COLLIDE-PRED models is shown in Figure 4.5. The mean accuracy of PCSMO (0.939) is significantly higher than that

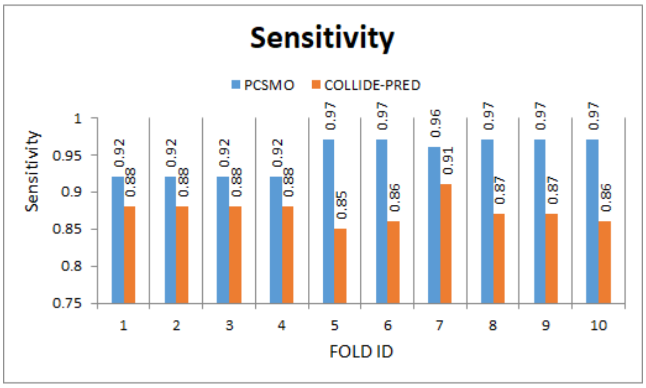


Fig. 4.4: The sensitivity observed from tenfold cross-validation

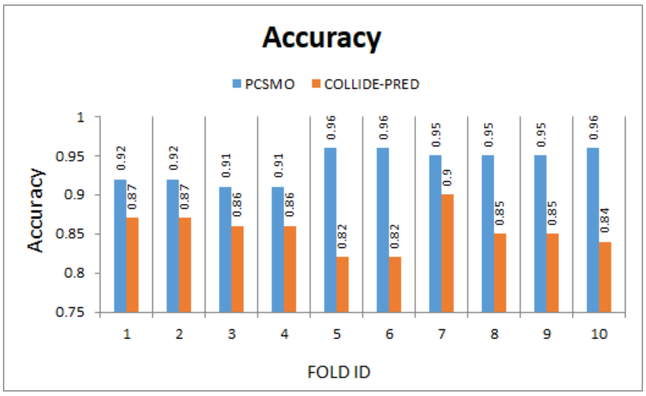


Fig. 4.5: Accuracy obtained from tenfold cross-validation

of COLLIDE-PRED (0.854), meaning that PCSMO correctly predicts both positive and negative outcomes more often than COLLIDE-PRED. In binary classification problems, the Matthews Correlation Coefficient (MCC) provides more information than accuracy when classes have significant differences in size. It evaluates negatives and true versus false positives and is thought to be balanced. PCSMO's MCC values exceeded COLLIDE-PRED's, demonstrating the predictive ability of the model.

The cross-validation metric MCC has been measured over the proposed and contemporary models among ten folds, as shown in Figure 4.6. The MCC observed for PCSMO and COLLIDE-PRED in the respective order. The detailed statistics of MCC obtained from tenfold cross-validation have been explored in Figure 4.6. The values obtained for metric MCC exhibits the significance of the PCSMO with better performance while compared to the contemporary model COLLIDE-PRED. PCSMO's mean MCC (0.875) is notably higher than COLLIDE-PRED's (0.714). Since MCC is a balanced measure even when the classes are of different sizes, a higher MCC indicates a better performance of PCSMO, with a stronger correlation between observed and predicted classifications.

**5. Conclusion.** In conclusion, it can be challenging to evaluate trajectories and locate intersections where moving objects might collide, particularly in road transportation where cars can travel in several directions. Potential collision zones between moving objects are predicted by Zero-shot Learning-based Trajectory Interception Classification. The potential collision locations and parameters between the primary and target objects are determined using angle-based analysis, which is incorporated into our PCSMO model. Threat zones are defined by overlapping Gann angles. After a thorough 10-fold cross-validation, the model's efficacy was determined.

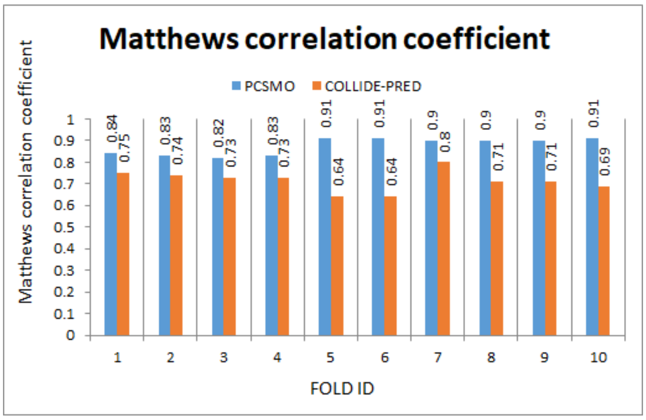


Fig. 4.6: The Mathews Correlation Coefficient (MCC) observed from the tenfold cross-validation

It fared significantly better than the COLLIDE-PRED model in every performance metric, with a prediction accuracy above 90%. From wide to narrow, the PCSMO model identifies the angle range and width of potential collision zones. The micro-level collision point is not precisely located by it. The Gann Nine scale approach will be added to this model in order to improve collision scope predictions. By using this refined scale, we hope to more accurately define the threat range and provide a second-level analysis that could significantly lower the risk of collisions. By defining threat zones, the Gann Nine square model extension will help us focus our predictive skills.

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