

Hackaton (Tech Challenge) - Pós-Tech - IA For Devs - FIAP

Fase 5 - Modelagem de ameaças utilizando IA

Alunos

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Evidências do projeto TODO

- Link para o repositório: [Repositorio Git](#)
- Link para o vídeo de apresentação: [Video Apresentação](#)

Bibliotecas utilizadas

- Principais bibliotecas:
 - **OpenCV (cv2)**: Biblioteca utilizada para manipulação de imagens.
 - **ultralytics**: Biblioteca utilizada para treinamento e manipulação do modelo Yolo11.
 - **Markdown**: Biblioteca para geração de relatórios básicos em formato Markdown e HTML.
 - **N8N**: Biblioteca utilizada para criação de workflows de automação.
 - **Flask**: Biblioteca utilizada para criação de API.

- Bibliotecas/ferramentas de suporte:
 - **Pytorch**: Biblioteca base para manipulação do modelo: [<https://pytorch.org/get-started/locally/>]
 - **Yolo**: Modelo utilizado pelo ultralytics na detecção de ícones AWS: [yolov11s.pt](#).
 - **Ollama**: Biblioteca para uso dos modelos de LLM do Ollama [<https://ollama.com/download/windows>]
 - **Telegram**: Plataforma de mensagens instantâneas, utilizada para interação com o usuário.
 - **Digital Ocean**: Plataforma de hospedagem de aplicações, utilizada para hospedar a API.
 - **N8N**: Plataforma de automação de workflows, utilizada para orquestrar as etapas do agente.

Preparação do Modelo de IA

Para realizar a detecção de diagramas de arquitetura, precisamos preparar um modelo para isto. A primeira etapa foi encontrar um dataset que nos ajudasse a treinar o modelo. Nossa busca levou ao dataset [AWS Icon Detector](#), que parecia promissor, mas necessitava de alguns ajustes.

O principal problema com este dataset é não possuir nenhum exemplo para validação. Outro grande problema é a disparidade entre os exemplos. Algumas classes possuem poucos exemplos como:

- `ACM`, com 3 para treinar e 1 para teste,

contrastando com

- `Lambda`, com 316 para treino e 10 para teste

ou

- `EC2`, com 213 para treino e 40 para teste.

Temos muitos casos, como - `Analytics Services`, que possui apenas 1 exemplo para treino e mais nenhum para teste.

Você pode verificar como o dataset original se distribui pelos diretórios de treino e teste, executando o seguinte script:

```
py dataset_report_samples_per_split.py
```

A execução do script, no [dataset original](#), mostra os seguintes valores por classe:

Classe	<code>id</code>	Train	Valid	Test
ACM	0	3	0	1
ALB	1	32	0	5
AMI	2	4	0	0
API-Gateway	3	163	0	0
Active Directory Service	4	1	0	1
Airflow	5	2	0	0
Amplify	6	8	0	0
Analytics Services	7	1	0	0
AppFlow	8	1	0	0
Appsync	9	5	0	0
Athena	10	10	0	1
Aurora	11	14	0	7
Auto Scaling	12	34	0	8
Auto Scaling Group	13	8	0	0
Automated Tests	14	6	0	0
Availability Zone	15	4	0	0
Backup	16	2	0	0
Build Environment	17	3	0	0
CDN	18	2	0	1
CUR	19	3	0	0
Call Metrics	20	1	0	0
Call Recordings	21	1	0	0
Certificate Manager	22	7	0	1
Client	23	7	0	0
Cloud Connector	24	2	0	0
Cloud Map	25	1	0	0
Cloud Search	26	3	0	1
Cloud Trail	27	16	0	3
Cloud Watch	28	70	0	7
CloudFormation Stack	29	15	0	1
CloudHSM	30	1	0	1
CloudWatch Alarm	31	11	0	0
Cloudfront	32	52	0	9
CodeBuild	33	21	0	1
CodeCommit	34	8	0	1
CodeDeploy	35	1	0	1
CodePipeline	36	20	0	0
Cognito	37	51	0	1
Comprehend	38	5	0	0
Config	39	6	0	6
Connect	40	1	0	0
Connect Contact Lens	41	1	0	0
Container	42	68	0	1
Control Tower	43	1	0	0
Customer Gateway	44	7	0	0
DSI	45	4	0	0
Data Pipeline	46	2	0	0
DataSync	47	2	0	0
Deploy Stage	48	2	0	0
Direct Connect	50	14	0	11
Docker Image	52	13	0	2
Dynamo DB	53	144	0	19
EBS	54	8	0	4
EC2	55	213	0	40
EFS	56	9	0	5
EFS Mount Target	57	8	0	9
EKS	58	15	0	0
ELB	59	77	0	13
Edge Location	61	4	0	3
ElastiCache	62	21	0	5

Elastic Container Registry	63	25	0	0
Elastic Container Service	64	38	0	2
Elastic Search	65	12	0	1
Elemental MediaConvert	66	3	0	1
Email	68	3	0	1
Endpoint	69	2	0	0
Event Bus	70	1	0	0
EventBridge	71	3	0	5
Experiment Duration	72	1	0	0
Experiments	73	1	0	0
Fargate	74	41	0	0
Fault Injection Simulator	75	3	0	0
Flask	77	3	0	0
GameLift	79	2	0	0
Git	80	1	0	0
Github	81	11	0	0
Glue	83	10	0	2
Glue DataBrew	84	2	0	0
Grafana	85	1	0	0
GuardDuty	86	4	0	5
IAM	87	27	0	9
IAM Role	88	16	0	7
IOT Core	89	7	0	1
Image	90	6	0	0
Image Builder	91	1	0	0
Ingress	92	1	0	0
Instances	94	2	0	0
Internet	95	41	0	8
Internet Gateway	96	19	0	4
Jenkins	97	2	0	0
Key Management Service	98	13	0	3
Kibana	99	1	0	0
Kinesis Data Streams	100	21	0	4
Kubernetes	101	1	0	0
Lambda	102	316	0	10
Lex	103	1	0	0
MQ	104	9	0	0
Machine Learning	105	4	0	0
Macie	106	5	0	4
Marketplace	107	2	0	0
Memcached	108	2	0	2
Mobile Client	109	28	0	4
Mongo DB	110	6	0	0
MySQL	111	1	0	0
NAT Gateway	112	36	0	8
Neptune	113	3	0	0
Network Adapter	114	1	0	0
Notebook	116	1	0	0
Order Controller	117	1	0	0
Organization Trail	118	1	0	4
Parameter Store	119	2	0	0
Pinpoint	120	1	0	0
PostgreSQL	121	1	0	0
Private Link	122	7	0	0
Private Subnet	123	101	0	10
Prometheus	124	1	0	0
Public Subnet	125	82	0	18
Quarkus	126	1	0	0
Quicksight	127	4	0	0
RDS	128	70	0	14
React	129	1	0	0
Redis	130	11	0	1

Redshift	131	6	0	1
Region	132	28	0	2
Rekognition	133	2	0	0
Results	134	1	0	0
Route 53	135	2	0	1
Route53	136	65	0	9
S3	137	225	0	24
SAR	138	1	0	0
SDK	139	31	0	1
SES	140	12	0	2
SNS	141	30	0	3
SQS	142	21	0	2
Sagemaker	144	27	0	0
Secret Manager	145	4	0	1
Security Group	146	1	0	1
Security Hub	147	1	0	5
Server	148	19	0	12
Service Catalog	149	6	0	0
Shield	150	3	0	1
Slack	152	2	0	0
Stack	154	2	0	0
Step Function	155	3	0	3
SwaggerHub	157	1	0	0
Systems Manager	158	3	0	2
TV	159	1	0	0
Table	160	19	0	0
Task Runner	161	1	0	0
Terraform	162	3	0	0
Text File	163	9	0	0
Textract	164	1	0	0
Transcribe	165	1	0	0
Transfer Family	166	6	0	0
Transit Gateway	167	2	0	0
Translate	168	3	0	0
Trusted Advisor	169	2	0	0
Twilio	170	1	0	0
Users	171	95	0	13
VDA	172	1	0	0
VP Gateway	173	4	0	1
VPC Router	174	11	0	6
VPN Connection	175	5	0	1
WAF	176	14	0	1
Web Clients	177	36	0	7
Websites	178	4	0	0
X-Ray	179	12	0	0
aws	180	136	0	13
cache Worker	181	2	0	0

Como pode ser notado, muitas classes não possuem testes e outras apenas 1 ou dois exemplos para treinamento.

Mas será que estes são os únicos problemas do dataset? O script abaixo faz algumas análises úteis:

```
py dataset_validation.py
```

Verificamos que o nc corresponde ao total de classes declaradas. No momento, temos 210 imagens e 210 labels. Não há nomes de classes duplicados, nc, imagens sem labels ou mesmo labels sem imagens. O resultado do script pode ser visto abaixo:

```

— Passo 1: contagens
nc declarado: 182
len(names): 182
total imagens: 210
total labels: 210
✓ nc == len(names)
✓ #imagens == #labels

— Passo 2: duplicatas em names
✓ Nenhuma duplicata em names

— Passo 3: consistência labels x names x imagens
✓ Todos os class_id em labels têm names associados

✓ Todas as imagens têm .txt correspondente
✓ Todos os labels têm imagem correspondente

✓ Todas as classes em names têm pelo menos 1 exemplo

```

Se decidirmos treinar o modelo com o dataset incompleto (isto é, com `valid/images` e `valid/labels` vazios), notaremos duas coisas:

```

[1]
WARNING Box and segment counts should be equal, but got len(segments) = 502,
len(boxes) = 3108. To resolve this only boxes will be used and all segments will
be removed. To avoid this please supply either a detect or segment dataset, not
a detect-segment mixed dataset.
albumentations: Blur(p=0.01, blur_limit=(3, 7)), MedianBlur(p=0.01,
blur_limit=(3, 7)), ToGray(p=0.01, method='weighted_average',
num_output_channels=3), CLAHE(p=0.01, clip_limit=(1.0, 4.0), tile_grid_size=(8, 8))
[2]
Traceback (most recent call last):
  File "D:\ia4devs\module_05\05_hackaton\venv\Lib\site-
    packages\ultralytics\data\base.py",
    line 178, in get_img_files
      assert im_files, f"{self.prefix}No images found in {img_path}.
      {FORMATS_HELP_MSG}"
      ^^^^^^^^
AssertionError: val: No images found in D:
    \ia4devs\module_05\05_hackaton\data\dataset\aws\valid\images.
Supported formats are:
images: {'heic', 'jpg', 'pfm', 'dng', 'mpo', 'bmp', 'jpeg', 'png', 'tiff', 'webp',
'tif'}
videos: {'mov', 'mkv', 'gif', 'ASF', 'ts', 'm4v', 'mpeg', 'webm', 'wmv', 'mpg', 'mp4',
'avi'}

```

[1] - Temos um aviso de que alguns rótulos nos arquivos de `label` estão inadequados. O formato de segmentação foi encontrado e o yolo vai descartar estas marcações.

[2] - O diretório `valid` deve conter imagens e labels.

Para corrigir [1], precisamos rodar o script:

```
py dataset_fix_labels.py
```

Para que ele detecte e corrija os rótulos inadequados. O resultado final será visto a seguir:

```
Fixed segments in: index101.jpg.rf.86ebe1a7bcfdd3fa92ef93ba5bfd2d19.txt
Fixed segments in: index108.png.rf.c04ccc21c4ad1c3f1ca51903606f7f0c.txt
Fixed segments in: index121.png.rf.71f9a36ddec18e197b04cc9cfc9e33c0.txt
Fixed segments in: index126.png.rf.a27b004ecd3aaae4b1d3a4747b69d613.txt
Fixed segments in: index136.png.rf.fd69f2a7634f5d83d4b09ace2ed4e8cd.txt
Fixed segments in: index137.jpg.rf.4a31794a0730be847e886f42f0fb7c94.txt
Fixed segments in: index154.jpg.rf.77cf8cc45b8a14d6fe9ea46e7f476f96.txt
Fixed segments in: index156.png.rf.b5d9270f67fd558d8e9036f3dfd575c0.txt
Fixed segments in: index161.png.rf.6c17459407b2e312e7adcc5649873ef9.txt
Fixed segments in: index177.png.rf.0cbfadbf1c1f8a322c3fcc7dd55e46a2.txt
Fixed segments in: index190.png.rf.ff2f24ed464240039309195bf0a73958.txt
Fixed segments in: index200.png.rf.3e34f6ab90231de27051ce831507656f.txt
Fixed segments in: index60.png.rf.1e092d82c19763160ffb6b2fdbf68fe.txt
Fixed segments in: index62.png.rf.a1dc5d4beaf0dce66f55b97b7218aa5a.txt
Fixed segments in: index67.png.rf.6101eff034895460da133f0a0c7bb7e9.txt
Fixed segments in: index69.png.rf.f31ae1094002aac0abf4942427ce17c3.txt
Fixed segments in: index72.png.rf.946082aea49f9d39dbfc714ab9a7becf.txt
Fixed segments in: index76.jpg.rf.acd014a7447bfd032a059df9a3c42ed2.txt
Fixed segments in: index78.jpg.rf.41ff895dc95a8301b653232b1f6076f7.txt
Fixed segments in: index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af.txt
Fixed segments in: index80.jpg.rf.ff8325243baab715ecc57e8b2816b32c.txt
Fixed segments in: index82.png.rf.59d98bc77a90b37701036d534176c12b.txt
Fixed segments in: index86.png.rf.1f930ebaa16216d58c45b42eed1980ff.txt
Fixed segments in: index87.png.rf.340a2720a19109394b7209a44a0a0560.txt
Fixed segments in: index93.png.rf.1b8824bdce863db0c370aa9e08dc6025.txt
Fixed segments in: index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601.txt
Fixed segments in: index97.png.rf.c7f0f49920f42b2c1ff635062a6db557.txt
Total files fixed: 27/189
Fixed segments in: index32.png.rf.1f5e0fbbf9b24e978afe47ad026cd451.txt
Fixed segments in: index40.png.rf.c25d82eaf131a966b05189d26ad5bcba.txt
Fixed segments in: index42.png.rf.fe55375b35dc8d5acb87b455aefe16a.txt
Fixed segments in: index43.jpg.rf.57e2088b019cbe2301f88be96faa8caf.txt
Fixed segments in: index45.png.rf.b8216c6948f9c7338bbc2d54c154b512.txt
Fixed segments in: index46.png.rf.a43f82f889300675176613a33f4e8168.txt
Fixed segments in: index5.png.rf.88b49ae013835d02145d6c80bce061fd.txt
Fixed segments in: index6.jpg.rf.f5a1f31d53e0577b2a9745e1f9b4f77b.txt
Total files fixed: 8/21
Total files fixed: 0/0
```

Para corrigir [2], precisamos rodar o script:

```
py dataset_rebalance_oversample.py
```

O script faz basicamente três coisas — geração de exemplos via oversampling, realocação para garantir ao menos um número mínimo de amostras em `valid` e em `test`, sempre mantendo sincronizados os arquivos de imagem e os de label. Na fase 1, o script garante, no mínimo, `MIN_TRAIN` instâncias de cada classe em `train`, duplicando (com oversampling de forma round-robin) pelas `bases` disponíveis. A cada nova imagem criada, também incrementa o contador e adiciona o novo `basename` ao conjunto. Na fase 2, garante pelo menos `MIN_VALID` instâncias em `valid`, movendo pares `imagem+label` de `train` (preferência) ou `test`. Na fase 3, assegura pelo menos `MIN_TEST` instâncias em `test`, movendo pares `imagem+label` de `train` (preferência) ou `valid`.

Abaixo, um log de exemplo da execução do script:

```
== Phase 1: Oversampling → TRAIN ==

Class 0: train has 70, target 70 → need 0
→ OK, não precisa oversample

Class 1: train has 48, target 70 → need 22
→ usando fonte train para oversample

(...)

Class 181: train has 2, target 70 → need 68
→ usando fonte train para oversample

== Phase 2: Rebalance → VALID ==

Class 0: valid has 0, min 15 → need 15
→ movendo de train para valid
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_5 from train →
valid
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_5 from train →
valid
→ movendo de train para valid
Moved IMAGE index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_24 from train →
valid
Moved LABEL index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_24 from train →
valid
→ movendo de train para valid
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_20 from train →
valid
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_20 from train →
valid
→ movendo de train para valid
Moved IMAGE index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_58 from train →
valid
Moved LABEL index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_58 from train →
valid
→ movendo de train para valid
Moved IMAGE index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_16 from train →
valid
Moved LABEL index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_16 from train →
valid
→ movendo de train para valid
Moved IMAGE index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_19 from train →
valid
Moved LABEL index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_19 from train →
valid
→ movendo de train para valid
Moved IMAGE index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_57 from train →
valid
Moved LABEL index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_57 from train →
valid
→ movendo de train para valid
Moved IMAGE index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_9 from train →
valid
Moved LABEL index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_9 from train →
valid
→ movendo de train para valid
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_11 from train →
valid
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_11 from train →
valid
→ movendo de train para valid
```

```
Moved IMAGE index93_png.rf.1b8824bdce863db0c370aa9e08dc6025_os_56 from train →  
valid  
Moved LABEL index93_png.rf.1b8824bdce863db0c370aa9e08dc6025_os_56 from train →  
valid  
→ movendo de train para valid  
Moved IMAGE index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_0 from train →  
valid  
Moved LABEL index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_0 from train →  
valid  
→ movendo de train para valid  
Moved IMAGE index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_36 from train →  
valid  
Moved LABEL index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_36 from train →  
valid  
→ movendo de train para valid  
Moved IMAGE index151_jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_55 from train →  
valid  
Moved LABEL index151_jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_55 from train →  
valid  
→ movendo de train para valid  
Moved IMAGE index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_27 from train →  
valid  
Moved LABEL index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_27 from train →  
valid  
→ movendo de train para valid  
Moved IMAGE index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_48 from train →  
valid  
Moved LABEL index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_48 from train →  
valid
```

(...)

```
Class 181: valid has 0, min 15 → need 15  
→ movendo de train para valid  
Moved IMAGE index161_png.rf.6c17459407b2e312e7adcc5649873ef9_os_29 from train →  
valid  
Moved LABEL index161_png.rf.6c17459407b2e312e7adcc5649873ef9_os_29 from train →  
valid  
→ movendo de train para valid  
Moved IMAGE index161_png.rf.6c17459407b2e312e7adcc5649873ef9_os_61 from train →  
valid  
Moved LABEL index161_png.rf.6c17459407b2e312e7adcc5649873ef9_os_61 from train →  
valid  
→ movendo de train para valid  
→ movendo de train para valid  
→ movendo de train para valid
```

==== Phase 3: Rebalance → TEST ===

```
Class 0: test has 1, min 15 → need 14  
→ movendo 'index79_jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_60' de train para  
test
```

```
Moved IMAGE index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_60 from train →  
test  
Moved LABEL index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_60 from train →  
test  
→ movendo 'index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_28' de train para  
test  
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_28 from train →  
test  
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_28 from train →  
test  
→ movendo 'index93.png.rf.1b8824bdce863db0c370aa9e08dc6025' de train para test  
→ movendo 'index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_48' de train para  
test  
Moved IMAGE index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_48 from train →  
test  
Moved LABEL index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_48 from train →  
test  
→ movendo 'index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_50' de train para  
test  
Moved IMAGE index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_50 from train →  
test  
Moved LABEL index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_50 from train →  
test  
→ movendo 'index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_40' de train para  
test  
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_40 from train →  
test  
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_40 from train →  
test  
→ movendo 'index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_49' de train para  
test  
→ movendo 'index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_37' de train para  
test  
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_37 from train →  
test  
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_37 from train →  
test  
→ movendo 'index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_4' de train para test  
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_4 from train →  
test  
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_4 from train →  
test  
→ movendo 'index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_2' de train para  
test  
Moved IMAGE index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_2 from train →  
test  
Moved LABEL index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_2 from train →  
test  
→ movendo 'index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_26' de train para  
test  
Moved IMAGE index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_26 from train →  
test  
Moved LABEL index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_26 from train →  
test  
→ movendo 'index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_41' de train para  
test  
Moved IMAGE index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_41 from train →  
test  
Moved LABEL index151.jpg.rf.9e63372d562634afb9a7d4bcef7c59f6_os_41 from train →  
test  
→ movendo 'index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_6' de train para test  
Moved IMAGE index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_6 from train →  
test
```

```

Moved LABEL index79.jpg.rf.4546d4d5cf54f6ddfb791a379783d3af_os_6 from train →
test
→ movendo 'index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_19' de train para
test
Moved IMAGE index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_19 from train →
test
Moved LABEL index93.png.rf.1b8824bdce863db0c370aa9e08dc6025_os_19 from train →
test
→ test agora tem 15 para classe 0

(...)

Class 181: test has 0, min 15 → need 15
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_39' de train para
test
→ movendo 'index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601_os_30' de train para
test
→ movendo 'index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601_os_8' de train para test
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_23' de train para
test
Moved IMAGE index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_23 from train →
test
Moved LABEL index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_23 from train →
test
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_31' de train para
test
→ movendo 'index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601_os_36' de train para
test
→ movendo 'index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601_os_6' de train para test
→ movendo 'index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601_os_16' de train para
test
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_19' de train para
test
Moved IMAGE index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_19 from train →
test
Moved LABEL index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_19 from train →
test
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_33' de train para
test
→ movendo 'index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601_os_38' de train para
test
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_67' de train para
test
Moved IMAGE index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_67 from train →
test
Moved LABEL index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_67 from train →
test
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_3' de train para
test
→ movendo 'index161.png.rf.6c17459407b2e312e7adcc5649873ef9_os_27' de train para
test
→ movendo 'index96.png.rf.50a8179a165b9e4dfa62dadcb03a7601_os_34' de train para
test
→ test agora tem 15 para classe 181

== Summary ==
Oversampled → TRAIN : 10484
Moved to VALID : 2730
Moved to TEST : 2345

```

Ao final, podemos verificar como ficou a distribuição de exemplos pelos três diretórios de trabalho. Executando o script abaixo novamente:

```
py dataset_report_samples_per_split.py
```

Podemos ver o trabalho efetuado na geração de um dataset útil para o treinamento do modelo e execução deste trabalho. O resultado pode ser comparado com o que foi obtido anteriormente, antes das mudanças que foram aplicadas, visando melhorar o treinamento:

Classe	id	Train	Valid	Test
ACM	0	120	62	42
ALB	1	746	332	292
AMI	2	109	44	39
API-Gateway	3	2798	1178	1063
Active Directory Service	4	81	31	29
Airflow	5	78	30	30
Amplify	6	198	84	76
Analytics Services	7	40	15	15
AppFlow	8	40	15	15
Appsync	9	120	61	50
Athena	10	328	148	141
Aurora	11	331	126	112
Auto Scaling	12	668	307	211
Auto Scaling Group	13	146	88	58
Automated Tests	14	198	98	89
Availability Zone	15	118	48	46
Backup	16	76	30	32
Build Environment	17	88	44	34
CDN	18	53	20	21
CUR	19	92	42	35
Call Metrics	20	40	15	15
Call Recordings	21	40	15	15
Certificate Manager	22	227	98	103
Client	23	124	61	61
Cloud Connector	24	80	32	28
Cloud Map	25	40	15	15
Cloud Search	26	127	56	48
Cloud Trail	27	434	192	142
Cloud Watch	28	1474	644	566
CloudFormation Stack	29	392	168	138
CloudHSM	30	74	34	33
CloudWatch Alarm	31	260	121	106
Cloudfront	32	943	427	366
CodeBuild	33	610	245	208
CodeCommit	34	192	80	66
CodeDeploy	35	41	17	13
CodePipeline	36	504	220	190
Cognito	37	876	391	354
Comprehend	38	153	72	73
Config	39	447	178	147
Connect	40	40	15	15
Connect Contact Lens	41	40	15	15
Container	42	812	346	403
Control Tower	43	39	17	14
Customer Gateway	44	148	74	62
DSI	45	126	68	62
Data Pipeline	46	61	23	22
DataSync	47	67	32	30
Deploy Stage	48	72	30	27
Detective	49	41	15	15
Direct Connect	50	329	126	112
Distribution	51	42	15	15
Docker Image	52	379	179	174
Dynamo DB	53	2352	979	958
EBS	54	330	147	107
EC2	55	4451	1935	1692
EFS	56	302	133	116
EFS Mount Target	57	349	129	128
EKS	58	413	184	164
ELB	59	1347	583	521

EMR	60	41	15	15
Edge Location	61	113	42	27
ElastiCache	62	299	170	121
Elastic Container Registry	63	502	235	212
Elastic Container Service	64	687	331	302
Elastic Search	65	310	147	117
Elemental MediaConvert	66	147	66	64
Elemental MediaPackage	67	41	15	15
Email	68	64	25	29
Endpoint	69	60	27	22
Event Bus	70	39	16	15
EventBridge	71	306	120	101
Experiment Duration	72	39	17	14
Experiments	73	39	17	14
Fargate	74	899	427	423
Fault Injection Simulator	75	105	49	45
Firewall Manager	76	41	15	15
Flask	77	114	45	51
Flow logs	78	164	60	60
GameLift	79	41	17	15
Git	80	38	15	17
Github	81	186	95	90
Glacier	82	41	15	15
Glue	83	260	116	118
Glue DataBrew	84	57	26	22
Grafana	85	36	20	14
GuardDuty	86	325	132	117
IAM	87	779	334	335
IAM Role	88	531	207	185
IOT Core	89	132	54	52
Image	90	154	74	63
Image Builder	91	40	15	15
Ingress	92	38	15	17
Inspector Agent	93	41	15	15
Instances	94	68	38	32
Internet	95	741	345	272
Internet Gateway	96	517	247	200
Jenkins	97	78	30	30
Key Management Service	98	351	155	139
Kibana	99	37	15	18
Kinesis Data Streams	100	483	198	207
Kubernetes	101	38	15	17
Lambda	102	5851	2489	2220
Lex	103	36	16	18
MQ	104	160	57	86
Machine Learning	105	121	56	47
Macie	106	369	146	119
Marketplace	107	49	21	19
Memcached	108	82	36	22
Mobile Client	109	543	249	196
Mongo DB	110	153	70	62
MySQL	111	40	15	15
NAT Gateway	112	802	375	293
Neptune	113	92	42	35
Network Adapter	114	40	15	15
Network Firewall	115	41	15	15
Notebook	116	37	18	15
Order Controller	117	35	18	17
Organization Trail	118	206	77	71
Parameter Store	119	74	26	27
Pinpoint	120	38	16	16
PostgreSQL	121	40	15	15

Private Link	122	204	89	87
Private Subnet	123	2330	930	936
Prometheus	124	36	20	14
Public Subnet	125	1809	841	715
Quarkus	126	36	20	14
Quicksight	127	107	51	50
RDS	128	1540	685	551
React	129	40	15	15
Redis	130	270	100	98
Redshift	131	200	80	72
Region	132	636	269	243
Rekognition	133	70	33	37
Results	134	39	17	14
Route 53	135	118	53	39
Route53	136	1413	611	532
S3	137	4902	2096	1862
SAR	138	38	18	14
SDK	139	802	403	301
SES	140	218	87	84
SNS	141	653	279	254
SQS	142	482	199	197
SSM Agent	143	41	15	15
Sagemaker	144	602	267	241
Secret Manager	145	123	46	44
Security Group	146	40	15	16
Security Hub	147	249	91	85
Server	148	502	193	165
Service Catalog	149	204	91	72
Shield	150	129	58	52
Sign-On	151	41	15	15
Slack	152	73	37	30
Snowball	153	41	15	15
Stack	154	52	22	14
Step Function	155	231	96	90
Storage Gateway	156	41	15	15
SwaggerHub	157	40	15	15
Systems Manager	158	181	76	68
TV	159	36	22	12
Table	160	478	196	154
Task Runner	161	35	18	17
Terraform	162	75	32	38
Text File	163	279	122	99
Textract	164	39	17	14
Transcribe	165	34	17	19
Transfer Family	166	151	68	67
Transit Gateway	167	74	35	31
Translate	168	108	49	53
Trusted Advisor	169	49	36	13
Twilio	170	37	15	18
Users	171	1858	790	656
VDA	172	40	16	14
VP Gateway	173	98	36	39
VPC Router	174	271	102	80
VPN Connection	175	106	57	48
WAF	176	290	131	109
Web Clients	177	605	248	268
Websites	178	85	31	34
X-Ray	179	232	95	112
aws	180	2810	1219	1067
cache Worker	181	68	36	26

Ainda temos classes com um número pequeno de exemplos, quando comparadas com outras que tem um número bem expressivo. Como comparativo, alguns números prévios, tomados ainda na fase aprimoramento do dataset:

```
🎯 Test Metrics (mean per class):
Precision: 0.470
Recall: 0.317
mAP@0.5: 0.318
mAP@0.5:0.95: 0.257
```

Já os mesmos números, tomados depois do aprimoramento do dataset, com o mesmo modelo, mostram como é importante dispor de um bom conjunto de exemplos para o treinamento de um modelo:

```
🎯 Test Metrics (mean per class):
Precision: 0.960
Recall: 0.996
mAP@0.5: 0.980
mAP@0.5:0.95: 0.950
```

Apresentando o contexto, os números iniciais foram obtidos pelo modelo **S**, após 200 épocas de treinamento. Comparativamente, o mesmo modelo, utilizando o dataset aprimorado, precisou de apenas 100 épocas para obter um resultado (precisão) muito superior.

Com isto, demos por encerrado o aprimoramento do dataset. O mesmo dataset também pode ser encontrado em [AWS Icon Detector Improved](#).

Partimos então para o treinamento dos modelos **Nano**, **Small** e **Medium**.

Treinamento do Yolo 11 - Modelo **N**

Para treinar o modelo, basta ajustar a variável abaixo:

```
yolo: str = 'yolo11n'
```

Depois, execute a chamada a seguir:

```
py model.py
```

Aguardar a conclusão do processo. O treinamento utilizou 100 épocas para treino, gastando 1,622 horas no processo. Um exemplo de log de execução pode ser visto abaixo:

```

Ultralytics 8.3.162 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060
    Laptop GPU, 8188MiB)
engine\trainer: agnostic_nms=False, amp=True, augment=True,
auto_augment=randaugment, batch=8, bgr=0.0, box=7.5, cache=False, cfg=None,
classes=None, close_mosaic=10, cls=0.5, conf=None, copy_paste=0.0,
copy_paste_mode=flip, cos_lr=False, cutmix=0.0, data=./data/dataset/aws/data.yaml,
degrees=0.0, deterministic=True, device=0, dfl=1.5, dnn=False, dropout=0.0,
dynamic=False, embed=None, epochs=100, erasing=0.4, exist_ok=False, flipr=0.5,
flipud=0.0, format=torchscript, fraction=1.0, freeze=None, half=False,
hsv_h=0.015, hsv_s=0.7, hsv_v=0.4, imgsz=640, int8=False, iou=0.7, keras=False,
kobj=1.0, line_width=None, lr0=0.0005, lrf=0.05, mask_ratio=4, max_det=300,
mixup=0.5, mode=train, model=./data/model/yolo11n.pt, momentum=0.937,
mosaic=1.0, multi_scale=True, name=yolo11n_custom_100, nbs=64, nms=False,
opset=None, optimize=False, optimizer=AdamW, overlap_mask=True, patience=10,
perspective=0.0, plots=True, pose=12.0, pretrained=True, profile=False,
project=None, rect=False, resume=False, retina_masks=False, save=True,
save_conf=False, save_crop=False,
save_dir=C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11n_custom_100,
save_frames=False, save_json=False, save_period=-1, save_txt=False, scale=0.5,
seed=0, shear=0.0, show=False, show_boxes=True, show_conf=True, show_labels=True,
simplify=True, single_cls=False, source=None, split=val, stream_buffer=False,
task=detect, time=None, tracker=botsort.yaml, translate=0.1, val=True,
verbose=True, vid_stride=1, visualize=False, warmup_bias_lr=0.1, warmup_epochs=3,
warmup_momentum=0.8, weight_decay=0.0005, workers=8, workspace=None
Overriding model.yaml nc=80 with nc=182

```

	from	n	params	module
	arguments			
0		-1 1	464	ultralytics.nn.modules.conv.Conv
	[3, 16, 3, 2]			
1		-1 1	4672	ultralytics.nn.modules.conv.Conv
	[16, 32, 3, 2]			
2		-1 1	6640	ultralytics.nn.modules.block.C3k2
	[32, 64, 1, False, 0.25]			
3		-1 1	36992	ultralytics.nn.modules.conv.Conv
	[64, 64, 3, 2]			
4		-1 1	26080	ultralytics.nn.modules.block.C3k2
	[64, 128, 1, False, 0.25]			
5		-1 1	147712	ultralytics.nn.modules.conv.Conv
	[128, 128, 3, 2]			
6		-1 1	87040	ultralytics.nn.modules.block.C3k2
	[128, 128, 1, True]			
7		-1 1	295424	ultralytics.nn.modules.conv.Conv
	[128, 256, 3, 2]			
8		-1 1	346112	ultralytics.nn.modules.block.C3k2
	[256, 256, 1, True]			
9		-1 1	164608	ultralytics.nn.modules.block.SPPF
	[256, 256, 5]			
10		-1 1	249728	ultralytics.nn.modules.block.C2PSA
	[256, 256, 1]			
11		-1 1	0	torch.nn.modules.upsampling.Upsample
	[None, 2, 'nearest']			
12		[-1, 6] 1	0	ultralytics.nn.modules.conv.Concat
	[1]			
13		-1 1	111296	ultralytics.nn.modules.block.C3k2
	[384, 128, 1, False]			
14		-1 1	0	torch.nn.modules.upsampling.Upsample
	[None, 2, 'nearest']			
15		[-1, 4] 1	0	ultralytics.nn.modules.conv.Concat
	[1]			
16		-1 1	32096	ultralytics.nn.modules.block.C3k2
	[256, 64, 1, False]			

```

17           -1 1    36992 ultralytics.nn.modules.conv.Conv
[64, 64, 3, 2]
18           [-1, 13] 1      0 ultralytics.nn.modules.conv.Concat
[1]
19           -1 1    86720 ultralytics.nn.modules.block.C3k2
[192, 128, 1, False]
20           -1 1    147712 ultralytics.nn.modules.conv.Conv
[128, 128, 3, 2]
21           [-1, 10] 1      0 ultralytics.nn.modules.conv.Concat
[1]
22           -1 1    378880 ultralytics.nn.modules.block.C3k2
[384, 256, 1, True]
23           [16, 19, 22] 1   521278 ultralytics.nn.modules.head.Detect
[182, [64, 128, 256]]
YOLO11n summary: 181 layers, 2,680,446 parameters, 2,680,430 gradients, 6.9 GFLOPs

```

```

Transferred 448/499 items from pretrained weights
Freezing layer 'model.23.dfl.conv.weight'
AMP: running Automatic Mixed Precision (AMP) checks...
Downloading https://github.com/ultralytics/assets/releases/download/v8.3.0/yolo11n.pt
to 'yolo11n.pt'...
100%|██████████| 5.35M/5.35M [00:03<00:00, 1.77MB/s]
AMP: checks passed
train: Fast image access (ping: 0.00.0 ms, read: 2741.9957.6 MB/s, size: 410.9 KB)
train: Scanning D:
    \ia4devs\module_05\05_hackaton\data\dataset\aws\train\labels.cache... 3457
    images, 0 backgrounds, 0 c
val: Fast image access (ping: 0.00.0 ms, read: 977.6420.3 MB/s, size: 204.4 KB)
val: Scanning D:\ia4devs\module_05\05_hackaton\data\dataset\aws\valid\labels.cache...
    1488 images, 0 backgrounds, 0 cor
Plotting labels to C:
    \acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11n_custom_100\labels.jpg...

```

```

optimizer: AdamW(lr=0.0005, momentum=0.937) with parameter groups 81
    weight(decay=0.0), 88 weight(decay=0.0005), 87 bias(decay=0.0)
Image sizes 640 train, 640 val
Using 8 dataloader workers
Logging results to C:
    \acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11n_custom_100
Starting training for 100 epochs...

```

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
1/100	6.44G	1.233	3.756	0.9746	32	864: 100%
	██████████ 433/433 [00:54<00:00,					
	Class	Images	Instances	Box(P	R	mAP50
mAP50-95): 100% ██████████ 93/93 [00:23						
	all	1488	30084	0.385	0.0828	0.0319
	0.0239					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
2/100	6.12G	1.14	2.761	0.9666	125	320: 100%
	██████████ 433/433 [00:48<00:00,					
	Class	Images	Instances	Box(P	R	mAP50
mAP50-95): 100% ██████████ 93/93 [00:09						
	all	1488	30084	0.643	0.138	0.12
	0.0872					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
3/100	4.7G	1.075	2.182	0.9515	24	480: 100%
	██████████ 433/433 [00:47<00:00,					
	Class	Images	Instances	Box(P	R	mAP50
mAP50-95): 100% ██████████ 93/93 [00:09						

	all	1488	30084	0.609	0.248	0.258
0.196						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
4/100	4.43G	1.049	1.896	0.9445	98	608: 100%
		██████████ 433/433 [00:47<00:00,				
		Class Images Instances	Box(P)	R	mAP50	
		mAP50-95): 100% ██████████ 93/93 [00:08				
		all 1488 30084	0.585	0.324	0.354	
0.269						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
5/100	5.45G	1.005	1.644	0.9351	78	640: 100%
		██████████ 433/433 [00:46<00:00,				
		Class Images Instances	Box(P)	R	mAP50	
		mAP50-95): 100% ██████████ 93/93 [00:08				
		all 1488 30084	0.643	0.426	0.461	
0.361						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
6/100	5.35G	0.9933	1.5	0.9282	30	896: 100%
		██████████ 433/433 [00:46<00:00,				
		Class Images Instances	Box(P)	R	mAP50	
		mAP50-95): 100% ██████████ 93/93 [00:08				
		all 1488 30084	0.624	0.515	0.57	
0.441						
<hr/>						
(...)						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
48/100	5.61G	0.7054	0.5857	0.862	23	896: 100%
		██████████ 433/433 [00:48<00:00,				
		Class Images Instances	Box(P)	R	mAP50	
		mAP50-95): 100% ██████████ 93/93 [00:08				
		all 1488 30084	0.954	0.982	0.981	
0.871						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
49/100	5.03G	0.7039	0.5761	0.8637	43	928: 100%
		██████████ 433/433 [00:50<00:00,				
		Class Images Instances	Box(P)	R	mAP50	
		mAP50-95): 100% ██████████ 93/93 [00:08				
		all 1488 30084	0.951	0.989	0.981	
0.874						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
50/100	3.88G	0.7042	0.5848	0.8582	17	416: 100%
		██████████ 433/433 [00:48<00:00,				
		Class Images Instances	Box(P)	R	mAP50	
		mAP50-95): 100% ██████████ 93/93 [00:08				
		all 1488 30084	0.955	0.986	0.98	
0.871						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
51/100	3.89G	0.6942	0.5689	0.863	41	832: 100%
		██████████ 433/433 [00:49<00:00,				
		Class Images Instances	Box(P)	R	mAP50	
		mAP50-95): 100% ██████████ 93/93 [00:08				
		all 1488 30084	0.955	0.987	0.98	
0.876						
<hr/>						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size

52/100	3.91G	0.6947	0.5699	0.8605	91	960: 100%
	[██████████ 433/433 [00:48<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100% ██████████ 93/93 [00:08					
	all	1488	30084	0.959	0.983	0.981
	0.878					
(...)						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
98/100	3.61G	0.4652	0.2971	0.8127	18	416: 100%
	[██████████ 433/433 [00:46<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100% ██████████ 93/93 [00:08					
	all	1488	30084	0.96	0.995	0.983
	0.911					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
99/100	3.61G	0.4553	0.2923	0.8131	30	896: 100%
	[██████████ 433/433 [00:46<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100% ██████████ 93/93 [00:08					
	all	1488	30084	0.961	0.994	0.984
	0.911					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
100/100	3.61G	0.4588	0.2938	0.8114	22	960: 100%
	[██████████ 433/433 [00:45<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100% ██████████ 93/93 [00:08					
	all	1488	30084	0.961	0.994	0.983
	0.912					
100 epochs completed in 1.622 hours.						
Optimizer stripped from C:						
	\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo1n_custom_100\weights\best.pt,					
	5.7MB					
Validating C:						
	\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo1n_custom_100\weights\best.pt...					
Ultralytics 8.3.162 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060 Laptop GPU, 8188MiB)						
YOLO1n summary (fused): 100 layers, 2,672,434 parameters, 0 gradients, 6.8 GFLOPs						
	Class	Images	Instances	Box(P)	R	mAP50mAP50-95): 100%
		93/93 [00:12				
	all	1488	30084	0.957	0.994	0.984
	ACM	62	62	0.989	1	0.995
	ALB	228	332	0.992	1	0.994
	AMI	29	44	0.982	1	0.995
	API-Gateway	774	1178	0.997	0.983	0.995
	Active Directory Service	31	31	0.984	1	0.995
	Airflow_	15	30	0.983	1	0.995
	Amplify	84	84	0.99	1	0.995
	Analytics Services	15	15	0.969	1	0.995
	AppFlow	15	15	0.969	1	0.995
	Appsync	61	61	0.989	1	0.995
	Athena	143	148	1	0.995	0.995
	Aurora	89	126	0.963	1	0.982
	Auto Scaling	173	307	0.984	0.993	0.995
	Auto Scaling Group	35	88	0.992	1	0.995
	Automated Tests	64	98	0.995	1	0.995
						0.917

Availability Zone	24	48	0.989	1	0.995	0.898
Backup	15	30	0.984	1	0.995	0.995
Build Environment	44	44	0.848	1	0.995	0.862
CDN	20	20	0.89	1	0.966	0.921
CUR	42	42	0.988	1	0.995	0.751
Call Metrics	15	15	0.97	1	0.995	0.887
Call Recordings	15	15	0.973	1	0.995	0.793
Certificate Manager	98	98	0.994	1	0.995	0.945
Client	16	61	0.671	0.702	0.74	0.649
Cloud Connector	16	32	0.982	1	0.995	0.877
Cloud Map	15	15	0.968	1	0.995	0.995
Cloud Search	56	56	0.801	1	0.995	0.893
Cloud Trail	187	192	0.997	1	0.995	0.903
Cloud Watch	543	644	0.986	1	0.995	0.906
CloudFormation Stack	150	168	0.995	1	0.995	0.929
CloudHSM	34	34	0.983	1	0.995	0.916
CloudWatch Alarm	87	121	0.996	1	0.995	0.882
Cloudfront	401	427	0.997	0.998	0.995	0.9
CodeBuild	157	245	0.997	1	0.995	0.94
CodeCommit	68	80	0.992	1	0.995	0.941
CodeDeploy	17	17	0.971	1	0.995	0.995
CodePipeline	214	220	0.998	1	0.995	0.915
Cognito	346	391	0.971	0.927	0.982	0.898
Comprehend	72	72	0.992	1	0.995	0.959
Config	103	178	0.903	0.993	0.982	0.873
Connect	15	15	0.969	1	0.995	0.962
Connect Contact Lens	15	15	0.964	1	0.995	0.902
Container	79	346	0.964	0.997	0.995	0.834
Control Tower	17	17	0.973	1	0.995	0.986
Customer Gateway	38	74	0.996	1	0.995	0.905
DSI	34	68	0.993	1	0.995	0.858
Data Pipeline	23	23	0.978	1	0.995	0.914
DataSync	32	32	0.985	1	0.995	0.995
Deploy Stage	30	30	0.978	1	0.995	0.848
Detective	15	15	0.967	1	0.995	0.922
Direct Connect	91	126	0.995	1	0.995	0.939
Distribution	15	15	0.603	1	0.947	0.927
Docker Image	56	179	0.953	0.904	0.983	0.744
Dynamo DB	660	979	0.997	1	0.995	0.915
EBS	92	147	0.936	0.993	0.995	0.846
EC2	707	1935	0.982	0.997	0.995	0.892
EFS	100	133	0.995	1	0.995	0.928
EFS Mount Target	99	129	0.995	1	0.995	0.877
EKS	161	184	0.996	1	0.995	0.926
ELB	425	583	0.997	0.966	0.97	0.907
EMR	15	15	0.968	1	0.995	0.922
Edge Location	20	42	0.989	1	0.995	0.978
ElastiCache	138	170	0.989	1	0.995	0.882
Elastic Container Registry	235	235	0.979	0.996	0.995	0.936
Elastic Container Service	258	331	0.998	1	0.995	0.866
Elastic Search	142	147	0.995	1	0.995	0.882
Elemental MediaConvert	49	66	0.898	0.802	0.961	0.951
Elemental MediaPackage	15	15	0.467	1	0.669	0.669
Email	25	25	0.98	1	0.995	0.912
Endpoint	27	27	0.973	1	0.995	0.815
Event Bus	16	16	0.962	1	0.995	0.995
EventBridge	60	120	0.915	1	0.994	0.89
Experiment Duration	17	17	0.565	1	0.772	0.597
Experiments	17	17	0.561	1	0.641	0.585
Fargate	193	427	0.999	1	0.995	0.885
Fault Injection Simulator	49	49	0.99	1	0.995	0.918
Firewall Manager	15	15	0.968	1	0.995	0.922

Flask	15	45	0.977	0.956	0.984	0.726
Flow logs	15	60	0.985	1	0.995	0.745
GameLift	17	17	0.973	1	0.995	0.93
Git	15	15	0.97	1	0.995	0.904
Github	81	95	0.986	1	0.995	0.911
Glacier	15	15	0.967	1	0.995	0.9
Glue	58	116	1	0.979	0.995	0.876
Glue DataBrew	26	26	0.982	1	0.995	0.969
Grafana	20	20	0.977	1	0.995	0.995
GuardDuty	72	132	0.996	1	0.995	0.843
IAM	201	334	0.83	1	0.985	0.844
IAM Role	98	207	0.823	0.965	0.971	0.776
IOT Core	40	54	0.991	1	0.995	0.969
Image	74	74	0.992	1	0.995	0.821
Image Builder	15	15	0.964	1	0.995	0.995
Ingress	15	15	0.97	1	0.995	0.989
Inspector Agent	15	15	0.969	1	0.995	0.834
Instances	19	38	0.554	0.98	0.661	0.587
Internet	240	345	0.949	1	0.994	0.907
Internet Gateway	167	247	0.965	1	0.995	0.836
Jenkins	15	30	0.984	1	0.995	0.97
Key Management Service	127	155	0.997	1	0.995	0.915
Kibana	15	15	0.97	1	0.995	0.845
Kinesis Data Streams	150	198	0.986	1	0.995	0.937
Kubernetes	15	15	0.97	1	0.995	0.918
Lambda	945	2489	0.994	0.997	0.995	0.919
Lex	16	16	0.97	1	0.995	0.995
MQ	25	57	0.991	1	0.995	0.869
Machine Learning	56	56	0.832	1	0.98	0.947
Macie	65	146	0.99	1	0.995	0.832
Marketplace	21	21	0.981	1	0.995	0.662
Memcached	18	36	0.976	1	0.995	0.923
Mobile Client	198	249	0.975	0.984	0.989	0.831
Mongo DB	26	70	0.971	0.957	0.994	0.775
MySQL	15	15	0.973	1	0.995	0.844
NAT Gateway	187	375	0.999	1	0.995	0.913
Neptune	42	42	0.991	1	0.995	0.679
Network Adapter	15	15	0.916	1	0.995	0.995
Network Firewall	15	15	0.968	1	0.995	0.986
Notebook	18	18	0.974	1	0.995	0.982
Order Controller	18	18	0.973	1	0.995	0.91
Organization Trail	32	77	0.992	1	0.995	0.873
Parameter Store	26	26	0.98	1	0.995	0.92
Pinpoint	16	16	0.97	1	0.995	0.973
PostgreSQL	15	15	0.964	1	0.995	0.911
Private Link	89	89	0.994	1	0.995	0.912
Private Subnet	368	930	0.982	0.967	0.986	0.798
Prometheus	20	20	0.976	1	0.995	0.922
Public Subnet	338	841	0.98	0.987	0.993	0.79
Quarkus	20	20	0.976	1	0.995	0.966
Quicksight	41	51	0.972	1	0.995	0.92
RDS	345	685	0.985	0.987	0.994	0.89
React	15	15	0.852	1	0.995	0.815
Redis	49	100	1	0.995	0.995	0.91
Redshift	73	80	0.994	1	0.995	0.868
Region	183	269	0.994	1	0.995	0.828
Rekognition	33	33	0.984	1	0.995	0.973
Results	17	17	0.564	1	0.737	0.681
Route 53	53	53	0.987	1	0.995	0.97
Route53	428	611	0.995	1	0.995	0.918
S3	977	2096	0.995	0.999	0.995	0.894
SAR	18	18	0.974	1	0.995	0.989

	SDK	123	403	0.972	0.995	0.995	0.89
	SES	72	87	0.994	1	0.995	0.895
	SNS	258	279	0.994	1	0.995	0.954
	SQS	189	199	0.997	1	0.995	0.913
	SSM Agent	15	15	0.969	1	0.995	0.967
	Sagemaker	81	267	0.985	1	0.995	0.731
	Secret Manager	46	46	0.987	1	0.995	0.924
	Security Group	15	15	0.967	1	0.995	0.995
	Security Hub	31	91	0.955	1	0.995	0.812
	Server	101	193	0.989	1	0.995	0.91
	Service Catalog	40	91	0.994	1	0.995	0.885
	Shield	58	58	0.991	1	0.995	0.966
	Sign-On	15	15	0.969	1	0.995	0.91
	Slack	37	37	0.984	1	0.995	0.923
	Snowball	15	15	0.969	1	0.995	0.984
	Stack	22	22	0.977	1	0.995	0.862
	Step Function	32	96	0.994	1	0.995	0.909
	Storage Gateway	15	15	0.966	1	0.995	0.902
	SwaggerHub	15	15	0.966	1	0.995	0.96
	Systems Manager	61	76	0.99	1	0.995	0.949
	TV	22	22	0.976	1	0.995	0.897
	Table	88	196	1	1	0.995	0.847
	Task Runner	18	18	0.97	1	0.995	0.905
	Terraform	32	32	0.986	1	0.995	0.874
	Text File	54	122	0.946	1	0.994	0.881
	Texttract	17	17	0.971	1	0.995	0.966
	Transcribe	17	17	0.972	1	0.995	0.909
	Transfer Family	68	68	0.993	1	0.995	0.954
	Transit Gateway	35	35	0.964	1	0.995	0.927
	Translate	49	49	0.99	1	0.995	0.96
	Trusted Advisor	36	36	0.987	1	0.995	0.952
	Twilio	15	15	0.969	1	0.995	0.987
	Users	574	790	0.994	0.971	0.992	0.87
	VDA	16	16	0.964	1	0.995	0.895
	VP Gateway	30	36	0.99	1	0.995	0.85
	VPC Router	50	102	0.933	1	0.995	0.894
	VPN Connection	21	57	0.99	1	0.995	0.917
	WAF	112	131	0.996	1	0.995	0.917
	Web Clients	213	248	0.784	1	0.983	0.826
	Websites	31	31	0.985	1	0.995	0.933
	X-Ray	83	95	0.995	1	0.995	0.911
	aws	971	1219	0.981	0.991	0.994	0.841
	cache Worker	36	36	0.982	1	0.995	0.933

Speed: 0.1ms preprocess, 4.4ms inference, 0.0ms loss, 1.1ms postprocess per image
 Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11n_custom_100

🚀 Save dir: C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11n_custom_100

✓ best.pt: C:

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Ultralytics 8.3.162 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060 Laptop GPU, 8188MiB)

YOLOv11n summary (fused): 100 layers, 2,672,434 parameters, 0 gradients, 6.8 GFLOPs

val: Fast image access (ping: 0.00.0 ms, read: 627.2396.8 MB/s, size: 365.8 KB)

val: Scanning D:\ia4devs\module_05\05_hackaton\data\dataset\aws\test\labels... 1327 images, 0 backgrounds, 0 corrupt: 1

val: New cache created: D:

\ia4devs\module_05\05_hackaton\data\dataset\aws\test\labels.cache

Class Images Instances Box(P R mAP50 mAP50-95): 100% |

███████████ | 166/166 [00:

all	1327	26828	0.957	0.992	0.979	0.911
ACM	42	42	0.984	1	0.995	0.99
ALB	206	292	0.968	0.983	0.993	0.891

	AMI	24	39	0.985	1	0.995	0.956
	API-Gateway	707	1063	1	0.981	0.995	0.93
Active Directory Service		29	29	0.982	1	0.995	0.985
	Airflow_	15	30	0.983	1	0.995	0.901
	Amplify	76	76	0.998	1	0.995	0.894
Analytics Services		15	15	0.967	1	0.995	0.978
	AppFlow	15	15	0.968	1	0.995	0.986
	Appsync	50	50	0.972	1	0.995	0.817
	Athena	133	141	1	0.979	0.995	0.939
	Aurora	79	112	0.983	0.964	0.968	0.933
Auto Scaling		126	211	0.996	0.976	0.989	0.826
Auto Scaling Group		25	58	0.988	1	0.995	0.848
Automated Tests		58	89	0.996	1	0.995	0.95
Availability Zone		23	46	0.987	1	0.995	0.935
Backup		16	32	0.983	1	0.995	0.995
Build Environment		34	34	0.89	1	0.995	0.845
CDN		21	21	0.974	1	0.995	0.976
CUR		35	35	0.985	1	0.995	0.79
Call Metrics		15	15	0.965	1	0.995	0.863
Call Recordings		15	15	0.976	1	0.995	0.859
Certificate Manager		103	103	0.995	1	0.995	0.987
	Client	16	61	0.559	0.82	0.686	0.612
Cloud Connector		14	28	0.979	1	0.995	0.919
	Cloud Map	15	15	0.966	1	0.995	0.995
Cloud Search		48	48	0.761	1	0.995	0.93
Cloud Trail		140	142	0.996	1	0.995	0.944
Cloud Watch		468	566	0.997	1	0.995	0.924
CloudFormation Stack		124	138	0.988	1	0.995	0.981
	CloudHSM	33	33	0.981	1	0.995	0.977
CloudWatch Alarm		75	106	0.995	1	0.995	0.886
	Cloudfront	346	366	0.996	1	0.995	0.91
CodeBuild		140	208	0.997	1	0.995	0.963
CodeCommit		52	66	0.992	1	0.995	0.983
CodeDeploy		13	13	0.96	1	0.995	0.988
CodePipeline		183	190	0.993	1	0.99	0.916
	Cognito	310	354	0.969	0.935	0.975	0.927
Comprehend		73	73	0.993	1	0.995	0.95
	Config	72	147	0.912	0.983	0.986	0.889
	Connect	15	15	0.967	1	0.995	0.984
Connect Contact Lens		15	15	0.97	1	0.995	0.942
	Container	86	403	0.988	1	0.995	0.861
Control Tower		14	14	0.964	1	0.995	0.976
Customer Gateway		35	62	0.996	1	0.995	0.929
	DSI	31	62	0.992	1	0.995	0.854
Data Pipeline		22	22	0.975	1	0.995	0.995
	DataSync	30	30	0.982	1	0.995	0.995
Deploy Stage		27	27	0.979	1	0.995	0.863
Detective		15	15	0.963	1	0.995	0.922
Direct Connect		77	112	0.995	0.991	0.995	0.914
	Distribution	15	15	0.594	1	0.849	0.822
Docker Image		44	174	0.993	0.877	0.984	0.76
	Dynamo DB	619	958	0.997	0.993	0.995	0.921
	EBS	65	107	0.931	0.963	0.992	0.825
	EC2	609	1692	0.982	0.987	0.994	0.904
	EFS	90	116	0.986	0.983	0.989	0.931
EFS Mount Target		95	128	1	0.925	0.981	0.905
	EKS	147	164	0.996	1	0.995	0.956
	ELB	379	521	0.996	0.956	0.97	0.912
	EMR	15	15	0.966	1	0.995	0.98
Edge Location		15	27	0.982	1	0.995	0.94
	ElastiCache	101	121	0.994	0.967	0.971	0.871
Elastic Container Registry		212	212	0.998	1	0.995	0.957

Elastic Container Service	236	302	0.995	1	0.995	0.9
Elastic Search	116	117	0.984	1	0.995	0.89
Elemental MediaConvert	49	64	0.853	0.938	0.97	0.955
Elemental MediaPackage	15	15	0.498	1	0.563	0.563
Email	29	29	0.98	0.966	0.969	0.871
Endpoint	22	22	0.975	1	0.995	0.846
Event Bus	15	15	0.963	1	0.995	0.995
EventBridge	41	101	0.912	0.99	0.993	0.923
Experiment Duration	14	14	0.552	0.88	0.559	0.489
Experiments	14	14	0.513	1	0.692	0.666
Fargate	180	423	0.999	1	0.995	0.923
Fault Injection Simulator	45	45	0.989	1	0.995	0.931
Firewall Manager	15	15	0.966	1	0.995	0.915
Flask	17	51	0.996	0.98	0.994	0.742
Flow logs	15	60	0.992	1	0.995	0.81
GameLift	15	15	0.966	1	0.995	0.933
Git	17	17	0.974	1	0.995	0.964
Github	73	90	0.995	1	0.995	0.928
Glacier	15	15	0.967	1	0.995	0.989
Glue	59	118	1	0.964	0.995	0.923
Glue DataBrew	22	22	0.976	1	0.995	0.995
Grafana	14	14	0.966	1	0.995	0.995
GuardDuty	57	117	0.998	1	0.995	0.904
IAM	180	335	0.921	0.994	0.991	0.889
IAM Role	78	185	0.843	0.984	0.98	0.816
IOT Core	46	52	1	0.991	0.995	0.988
Image	63	63	0.99	1	0.995	0.843
Image Builder	15	15	0.966	1	0.995	0.984
Ingress	17	17	0.971	1	0.995	0.995
Inspector Agent	15	15	0.968	1	0.995	0.995
Instances	16	32	0.517	1	0.536	0.476
Internet	201	272	0.947	0.993	0.993	0.915
Internet Gateway	133	200	0.996	0.99	0.995	0.836
Jenkins	15	30	0.982	1	0.995	0.969
Key Management Service	111	139	0.997	1	0.995	0.965
Kibana	18	18	0.983	1	0.995	0.899
Kinesis Data Streams	156	207	0.995	0.986	0.995	0.946
Kubernetes	17	17	0.971	1	0.995	0.957
Lambda	830	2220	0.995	0.995	0.995	0.939
Lex	18	18	0.971	1	0.995	0.995
MQ	34	86	0.994	1	0.995	0.899
Machine Learning	47	47	0.805	1	0.981	0.933
Macie	56	119	0.983	0.977	0.994	0.911
Marketplace	19	19	0.979	1	0.995	0.689
Memcached	11	22	0.895	1	0.995	0.943
Mobile Client	150	196	0.987	0.98	0.986	0.848
Mongo DB	26	62	1	0.986	0.995	0.783
MySQL	15	15	0.974	1	0.995	0.9
NAT Gateway	147	293	0.987	0.986	0.988	0.919
Neptune	35	35	0.988	1	0.995	0.708
Network Adapter	15	15	0.949	1	0.995	0.995
Network Firewall	15	15	0.966	1	0.995	0.995
Notebook	15	15	0.965	1	0.995	0.995
Order Controller	17	17	0.97	1	0.995	0.905
Organization Trail	26	71	0.992	1	0.995	0.934
Parameter Store	27	27	0.978	1	0.995	0.94
Pinpoint	16	16	0.969	1	0.995	0.995
PostgreSQL	15	15	0.962	1	0.995	0.919
Private Link	87	87	0.994	1	0.995	0.967
Private Subnet	335	936	0.994	0.966	0.985	0.83
Prometheus	14	14	0.964	1	0.995	0.995
Public Subnet	299	715	0.995	0.976	0.994	0.823

Quarkus	14	14	0.962	1	0.995	0.995
Quicksight	40	50	0.986	1	0.995	0.966
RDS	266	551	0.972	0.975	0.977	0.898
React	15	15	0.838	0.933	0.973	0.756
Redis	47	98	1	0.996	0.995	0.975
Redshift	65	72	0.993	1	0.995	0.945
Region	161	243	1	1	0.995	0.876
Rekognition	37	37	0.986	1	0.995	0.981
Results	14	14	0.517	1	0.555	0.525
Route 53	39	39	0.957	1	0.993	0.98
Route53	376	532	0.992	0.991	0.993	0.926
S3	867	1862	0.999	0.995	0.995	0.916
SAR	14	14	0.964	1	0.995	0.99
SDK	98	301	0.974	0.999	0.993	0.887
SES	69	84	0.991	0.988	0.995	0.932
SNS	232	254	0.998	0.996	0.995	0.967
SQS	184	197	0.997	1	0.995	0.956
SSM Agent	15	15	0.966	1	0.995	0.995
Sagemaker	76	241	0.999	1	0.995	0.736
Secret Manager	44	44	0.986	1	0.995	0.957
Security Group	16	16	0.969	1	0.995	0.966
Security Hub	25	85	0.994	1	0.995	0.897
Server	88	165	0.995	1	0.995	0.904
Service Catalog	30	72	0.994	1	0.995	0.907
Shield	52	52	0.991	1	0.995	0.963
Sign-On	15	15	0.966	1	0.995	0.934
Slack	30	30	0.98	1	0.995	0.983
Snowball	15	15	0.968	1	0.995	0.995
Stack	14	14	0.967	1	0.995	0.908
Step Function	30	90	0.994	1	0.995	0.92
Storage Gateway	15	15	0.965	1	0.995	0.97
SwaggerHub	15	15	0.971	1	0.995	0.965
Systems Manager	53	68	0.987	1	0.995	0.99
TV	12	12	0.956	1	0.995	0.912
Table	72	154	0.991	0.987	0.995	0.88
Task Runner	17	17	0.97	1	0.995	0.995
Terraform	38	38	0.989	1	0.995	0.864
Text File	49	99	0.949	0.899	0.97	0.866
Textract	14	14	0.965	1	0.995	0.995
Transcribe	19	19	0.974	1	0.995	0.995
Transfer Family	67	67	0.993	1	0.995	0.985
Transit Gateway	31	31	0.962	1	0.995	0.895
Translate	53	53	0.99	1	0.995	0.959
Trusted Advisor	13	13	0.958	1	0.995	0.964
Twilio	18	18	0.971	1	0.995	0.98
Users	486	656	0.995	0.98	0.987	0.893
VDA	14	14	0.966	1	0.995	0.912
VP Gateway	27	39	0.989	0.974	0.984	0.841
VPC Router	39	80	0.98	1	0.995	0.879
VPN Connection	21	48	0.997	1	0.995	0.91
WAF	99	109	0.995	1	0.995	0.968
Web Clients	202	268	0.795	1	0.971	0.84
Websites	34	34	0.99	1	0.995	0.953
X-Ray	88	112	1	0.988	0.995	0.953
aws	845	1067	0.982	0.986	0.992	0.87
cache Worker	26	26	0.981	1	0.995	0.995

Speed: 0.2ms preprocess, 2.7ms inference, 0.0ms loss, 1.0ms postprocess per image

Saving C:\acmattos\dev\tools\Python\ia4devs\runs\detect\val\predictions.json...

Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\val

🎯 Test Metrics (mean per class):

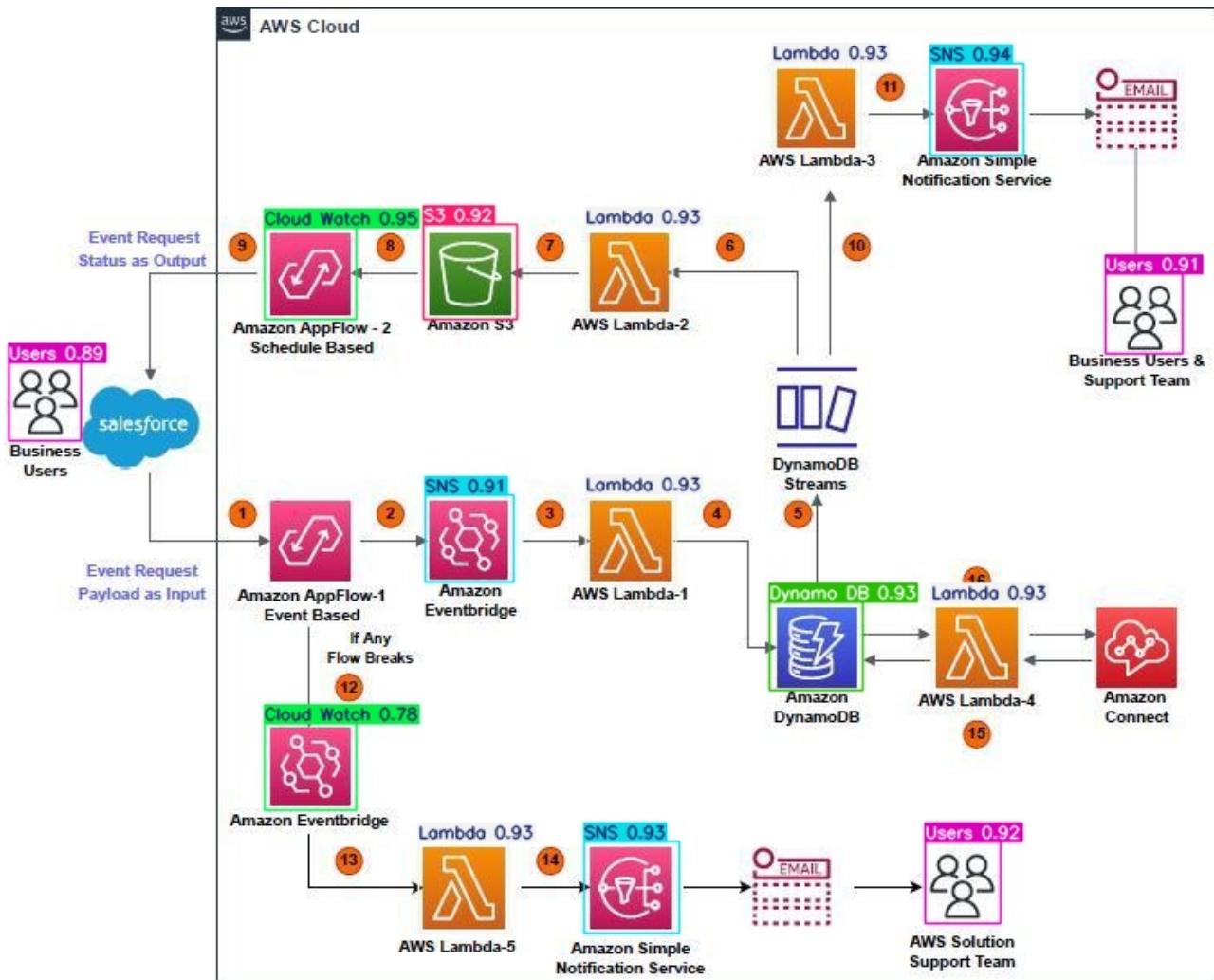
Precision: 0.957

```
Recall:      0.992
mAP@0.5:    0.979
mAP@0.5:0.95: 0.911

image 1/1 D:\ia4devs\module_05\05_hackaton\data\sample\aws_02.png: 576x640
1 ALB, 1 Auto Scaling, 1 Auto Scaling Group, 2 Cloud Watchs, 1 Cloudfront, 4 EC2s,
1 EFS, 1 Key Management Service, 2 NAT Gateways, 3 Private Subnets, 3 Public Subnets,
1 RDS, 1 Region, 1 Users, 2 WAFs, 1 aws, 47.2ms
Speed: 3.3ms preprocess, 47.2ms inference, 5.2ms postprocess per image at shape (1,
            3, 576, 640)
Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict
1 label saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict\labels
✓ Detailed JSON saved to data\reports\yolo11n_custom_100\results.json
✓ Summary JSON saved to data\reports\yolo11n_custom_100\report.json
[ultralytics.engine.results.Results object with attributes:

boxes: ultralytics.engine.results.Boxes object
keypoints: None
masks: None
(...)
obb: None
(...)
path: 'D:\\ia4devs\\module_05\\05_hackaton\\data\\\\sample\\\\aws_02.png'
probs: None
save_dir: 'C:\\acmattos\\dev\\tools\\Python\\ia4devs\\runs\\detect\\predict'
speed: {'preprocess': 3.2868999987840652, 'inference': 47.22200002288446,
        'postprocess': 5.245600012131035}]
```

Predição do Yolo 11 - Modelo N



Detecção do Modelo N

Treinamento do Yolo 11 - Modelo S

Para treinar o modelo, basta ajustar a variável abaixo:

```
yolo: str = 'yolo11s'
```

Depois, execute a chamada a seguir:

```
py model.py
```

Aguardar a conclusão do processo. O treinamento utilizou 100 épocas para treino, gastando 4.872 horas no processo. Um exemplo de log de execução pode ser visto abaixo:

```

Ultralytics 8.3.162 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060
    Laptop GPU, 8188MiB)
engine\trainer: agnostic_nms=False, amp=True, augment=True,
auto_augment=randaugment, batch=8, bgr=0.0, box=7.5, cache=False, cfg=None,
classes=None, close_mosaic=10, cls=0.5, conf=None, copy_paste=0.0,
copy_paste_mode=flip, cos_lr=False, cutmix=0.0, data=./data/dataset/aws/data.yaml,
degrees=0.0, deterministic=True, device=0, dfl=1.5, dnn=False, dropout=0.0,
dynamic=False, embed=None, epochs=100, erasing=0.4, exist_ok=False, flipr=0.5,
flipud=0.0, format=torchscript, fraction=1.0, freeze=None, half=False,
hsv_h=0.015, hsv_s=0.7, hsv_v=0.4, imgsz=640, int8=False, iou=0.7, keras=False,
kobj=1.0, line_width=None, lr0=0.0005, lrf=0.05, mask_ratio=4, max_det=300,
mixup=0.5, mode=train, model=./data/model/yolo11s.pt, momentum=0.937,
mosaic=1.0, multi_scale=True, name=yolo11s_custom_100, nbs=64, nms=False,
opset=None, optimize=False, optimizer=AdamW, overlap_mask=True, patience=10,
perspective=0.0, plots=True, pose=12.0, pretrained=True, profile=False,
project=None, rect=False, resume=False, retina_masks=False, save=True,
save_conf=False, save_crop=False,
save_dir=C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100,
save_frames=False, save_json=False, save_period=-1, save_txt=False, scale=0.5,
seed=0, shear=0.0, show=False, show_boxes=True, show_conf=True, show_labels=True,
simplify=True, single_cls=False, source=None, split=val, stream_buffer=False,
task=detect, time=None, tracker=botsort.yaml, translate=0.1, val=True,
verbose=True, vid_stride=1, visualize=False, warmup_bias_lr=0.1, warmup_epochs=3,
warmup_momentum=0.8, weight_decay=0.0005, workers=8, workspace=None
Overriding model.yaml nc=80 with nc=182

```

	from	n	params	module	arguments
0	-1	1	928	ultralytics.nn.modules.conv.Conv	[3, 32, 3, 2]
1	-1	1	18560	ultralytics.nn.modules.conv.Conv	[32, 64, 3, 2]
2	-1	1	26080	ultralytics.nn.modules.block.C3k2	[64, 128, 1,
	False,	0.25]			
3	-1	1	147712	ultralytics.nn.modules.conv.Conv	[128, 128, 3, 2]
4	-1	1	103360	ultralytics.nn.modules.block.C3k2	[128, 256, 1,
	False,	0.25]			
5	-1	1	590336	ultralytics.nn.modules.conv.Conv	[256, 256, 3, 2]
6	-1	1	346112	ultralytics.nn.modules.block.C3k2	[256, 256, 1,
	True]				
7	-1	1	1180672	ultralytics.nn.modules.conv.Conv	[256, 512, 3, 2]
8	-1	1	1380352	ultralytics.nn.modules.block.C3k2	[512, 512, 1,
	True]				
9	-1	1	656896	ultralytics.nn.modules.block.SPPF	[512, 512, 5]
10	-1	1	990976	ultralytics.nn.modules.block.C2PSA	[512, 512, 1]
11	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2,
	'nearest'				
12	[-1, 6]	1	0	ultralytics.nn.modules.conv.Concat	[1]
13	-1	1	443776	ultralytics.nn.modules.block.C3k2	[768, 256, 1,
	False]				
14	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2,
	'nearest'				
15	[-1, 4]	1	0	ultralytics.nn.modules.conv.Concat	[1]
16	-1	1	127680	ultralytics.nn.modules.block.C3k2	[512, 128, 1,
	False]				
17	-1	1	147712	ultralytics.nn.modules.conv.Conv	[128, 128, 3, 2]
18	[-1, 13]	1	0	ultralytics.nn.modules.conv.Concat	[1]
19	-1	1	345472	ultralytics.nn.modules.block.C3k2	[384, 256, 1,
	False]				
20	-1	1	590336	ultralytics.nn.modules.conv.Conv	[256, 256, 3, 2]
21	[-1, 10]	1	0	ultralytics.nn.modules.conv.Concat	[1]
22	-1	1	1511424	ultralytics.nn.modules.block.C3k2	[768, 512, 1,
	True]				
23	[16, 19, 22]	1	889842	ultralytics.nn.modules.head.Detect	[182, [128, 256,
	512]]				

```
YOLO11s summary: 181 layers, 9,498,226 parameters, 9,498,210 gradients, 21.9 GFLOPs
```

```
Transferred 493/499 items from pretrained weights
```

```
Freezing layer 'model.23.dfl.conv.weight'
```

```
AMP: running Automatic Mixed Precision (AMP) checks...
```

```
AMP: checks passed
```

```
train: Fast image access (ping: 0.10.0 ms, read: 344.2160.3 MB/s, size: 410.9 KB)
train: Scanning D:
```

```
    \ia4devs\module_05\05_hackaton\data\dataset\aws\train\labels.cache... 3457
    images, 0 backgrounds, 0 c
```

```
val: Fast image access (ping: 0.00.0 ms, read: 415.3126.7 MB/s, size: 204.4 KB)
```

```
val: Scanning D:\ia4devs\module_05\05_hackaton\data\dataset\aws\valid\labels.cache...
    1488 images, 0 backgrounds, 0 cor
```

```
Plotting labels to C:
```

```
    \acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100\labels.jpg...
```

```
optimizer: AdamW(lr=0.0005, momentum=0.937) with parameter groups 81
    weight(decay=0.0), 88 weight(decay=0.0005), 87 bias(decay=0.0)
```

```
Image sizes 640 train, 640 val
```

```
Using 8 dataloader workers
```

```
Logging results to C:
```

```
    \acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100
```

```
Starting training for 100 epochs...
```

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
1/100	7.99G	1.148	2.744	0.9568	32	864: 100%
	[██████████]	433/433 [03:05<00:00,				
		Class Images Instances		Box(P)	R	mAP50
		mAP50-95): 100% [██████████]	93/93 [00:40			
		all 1488	30084	0.546	0.199	0.18
						0.133

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
2/100	8.17G	1.024	1.643	0.9337	125	320: 100%
	[██████████]	433/433 [03:56<00:00,				
		Class Images Instances		Box(P)	R	mAP50
		mAP50-95): 100% [██████████]	93/93 [00:32			
		all 1488	30084	0.649	0.431	0.49
						0.363

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
3/100	6.62G	0.9507	1.235	0.9159	24	480: 100%
	[██████████]	433/433 [02:24<00:00,				
		Class Images Instances		Box(P)	R	mAP50
		mAP50-95): 100% [██████████]	93/93 [00:31			
		all 1488	30084	0.728	0.611	0.703
						0.535

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
4/100	6.47G	0.9155	1.038	0.9073	98	608: 100%
	[██████████]	433/433 [02:24<00:00,				
		Class Images Instances		Box(P)	R	mAP50
		mAP50-95): 100% [██████████]	93/93 [00:31			
		all 1488	30084	0.786	0.758	0.848
						0.686

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
5/100	7.34G	0.8713	0.8872	0.8983	78	640: 100%
	[██████████]	433/433 [02:24<00:00,				
		Class Images Instances		Box(P)	R	mAP50
		mAP50-95): 100% [██████████]	93/93 [00:31			
		all 1488	30084	0.87	0.876	0.938
						0.767

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
6/100	7.42G	0.8463	0.8025	0.8909	30	896: 100%
	[██████████]	433/433 [02:42<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100%	[██████████]	93/93 [00:31			
	all	1488	30084	0.868	0.869	0.938
	0.768					
7/100	6.64G	0.8276	0.7553	0.8904	35	800: 100%
	[██████████]	433/433 [02:27<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100%	[██████████]	93/93 [00:31			
	all	1488	30084	0.896	0.928	0.965
	0.801					
(...)						
48/100	7.63G	0.515	0.37	0.818	23	896: 100%
	[██████████]	433/433 [02:06<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100%	[██████████]	93/93 [00:24			
	all	1488	30084	0.967	0.989	0.983
	0.925					
49/100	7.17G	0.5161	0.3662	0.8196	43	928: 100%
	[██████████]	433/433 [02:16<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100%	[██████████]	93/93 [00:19			
	all	1488	30084	0.962	0.99	0.982
	0.92					
50/100	5.74G	0.5183	0.3713	0.8174	17	416: 100%
	[██████████]	433/433 [01:59<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100%	[██████████]	93/93 [00:30			
	all	1488	30084	0.966	0.992	0.982
	0.919					
51/100	6.08G	0.5072	0.3612	0.8181	41	832: 100%
	[██████████]	433/433 [02:12<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100%	[██████████]	93/93 [00:26			
	all	1488	30084	0.962	0.995	0.984
	0.93					
52/100	6.55G	0.5098	0.362	0.8175	91	960: 100%
	[██████████]	433/433 [02:18<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
	mAP50-95): 100%	[██████████]	93/93 [00:30			
	all	1488	30084	0.974	0.985	0.983
	0.927					
(...)						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size

99/100	5.69G	0.2881	0.1915	0.7826	30	896: 100%
		433/433 [02:17<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100%			93/93 [00:29			
	all	1488	30084	0.962	0.997	0.981
						0.949
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
100/100	5.57G	0.2896	0.1916	0.781	22	960: 100%
		433/433 [02:14<00:00,				
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100%			93/93 [00:31			
	all	1488	30084	0.962	0.997	0.982
						0.949

100 epochs completed in 4.872 hours.

Optimizer stripped from C:

```
\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100\weights\last.pt,
19.3MB
```

Optimizer stripped from C:

```
\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100\weights\best.pt,
19.3MB
```

Validating C:

```
\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100\weights\best.pt...
```

Ultralytics 8.3.162 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060 Laptop GPU, 8188MiB)

YOLOv11s summary (fused): 100 layers, 9,483,234 parameters, 0 gradients, 21.7 GFLOPs

	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100%		93/93 [00:45				
	all	1488	30084	0.962	0.995	
0.982	0.93					
	ACM	62	62	0.992	1	
0.995	0.994					
	ALB	228	332	0.999	1	
0.995	0.938					
	AMI	29	44	0.987	1	
0.995	0.98					
	API-Gateway	774	1178	0.974	0.992	
0.994	0.952					
	Active Directory Service	31	31	0.983	1	
0.995	0.975					
	Airflow_	15	30	0.984	1	
0.995	0.969					
	Amplify	84	84	0.982	1	
0.995	0.852					
	Analytics Services	15	15	0.969	1	
0.995	0.905					
	AppFlow	15	15	0.969	1	
0.995	0.995					
	Appsync	61	61	0.993	1	
0.995	0.824					
	Athena	143	148	0.819	1	
0.995	0.942					
	Aurora	89	126	0.976	1	
0.995	0.974					
	Auto Scaling	173	307	0.998	1	
0.995	0.929					
	Auto Scaling Group	35	88	0.995	1	
0.995	0.847					

	Automated Tests	64	98	0.995	1
0.995	0.945				
	Availability Zone	24	48	0.985	1
0.995	0.979				
	Backup	15	30	0.984	1
0.995	0.995				
	Build Environment	44	44	0.989	1
0.995	0.863				
	CDN	20	20	0.89	1
0.913	0.897				
	CUR	42	42	0.99	1
0.995	0.814				
	Call Metrics	15	15	0.969	1
0.995	0.89				
	Call Recordings	15	15	0.969	1
0.995	0.9				
	Certificate Manager	98	98	0.995	1
0.995	0.969				
	Client	16	61	0.709	0.52
0.788	0.682				
	Cloud Connector	16	32	0.985	1
0.995	0.933				
	Cloud Map	15	15	0.968	1
0.995	0.995				
	Cloud Search	56	56	0.991	1
0.995	0.918				
	Cloud Trail	187	192	0.997	1
0.995	0.979				
	Cloud Watch	543	644	0.999	1
0.995	0.942				
	CloudFormation Stack	150	168	0.997	1
0.995	0.968				
	CloudHSM	34	34	0.985	1
0.995	0.982				
	CloudWatch Alarm	87	121	0.996	1
0.995	0.933				
	Cloudfront	401	427	0.985	0.929
0.993	0.947				
	CodeBuild	157	245	0.998	1
0.995	0.94				
	CodeCommit	68	80	0.994	1
0.995	0.989				
	CodeDeploy	17	17	0.972	1
0.995	0.995				
	CodePipeline	214	220	0.998	1
0.995	0.928				
	Cognito	346	391	0.964	0.89
0.986	0.939				
	Comprehend	72	72	0.992	1
0.995	0.995				
	Config	103	178	0.921	0.978
0.993	0.902				
	Connect	15	15	0.968	1
0.995	0.98				
	Connect Contact Lens	15	15	0.965	1
0.995	0.921				
	Container	79	346	0.997	1
0.995	0.916				
	Control Tower	17	17	0.972	1
0.995	0.98				
	Customer Gateway	38	74	0.993	1
0.995	0.967				
	DSI	34	68	0.993	1
0.995	0.877				

	Data Pipeline	23	23	0.978	1
0.995	0.882				
	DataSync	32	32	0.985	1
0.995	0.992				
	Deploy Stage	30	30	0.985	1
0.995	0.878				
	Detective	15	15	0.969	1
0.995	0.963				
	Direct Connect	91	126	0.996	1
0.995	0.95				
	Distribution	15	15	0.615	1
0.92	0.9				
	Docker Image	56	179	0.967	1
0.995	0.826				
	Dynamo DB	660	979	0.963	1
0.995	0.96				
	EBS	92	147	0.999	1
0.995	0.925				
	EC2	707	1935	0.985	1
0.995	0.941				
	EFS	100	133	0.996	1
0.995	0.977				
	EFS Mount Target	99	129	0.996	1
0.995	0.93				
	EKS	161	184	0.992	1
0.995	0.975				
	ELB	425	583	0.999	0.969
0.975	0.944				
	EMR	15	15	0.968	1
0.995	0.995				
	Edge Location	20	42	0.988	1
0.995	0.97				
	ElastiCache	138	170	0.991	1
0.995	0.967				
	Elastic Container Registry	235	235	0.998	1
0.995	0.951				
	Elastic Container Service	258	331	0.991	0.993
0.995	0.893				
	Elastic Search	142	147	0.997	1
0.995	0.935				
	Elemental MediaConvert	49	66	0.83	0.962
0.963	0.963				
	Elemental MediaPackage	15	15	0.467	1
0.572	0.572				
	Email	25	25	0.98	1
0.995	0.969				
	Endpoint	27	27	0.983	1
0.995	0.98				
	Event Bus	16	16	0.967	1
0.995	0.995				
	EventBridge	60	120	0.996	1
0.995	0.9				
	Experiment Duration	17	17	0.566	1
0.588	0.559				
	Experiments	17	17	0.563	1
0.803	0.782				
	Fargate	193	427	0.973	1
0.995	0.932				
	Fault Injection Simulator	49	49	0.99	1
0.995	0.916				
	Firewall Manager	15	15	0.969	1
0.995	0.995				
	Flask	15	45	0.987	1
0.995	0.809				

	Flow logs	15	60	0.992	1
0.995	0.835				
	Gamelift	17	17	0.973	1
0.995	0.904				
	Git	15	15	0.969	1
0.995	0.911				
	Github	81	95	0.995	1
0.995	0.939				
	Glacier	15	15	0.968	1
0.995	0.987				
	Glue	58	116	0.995	1
0.995	0.94				
	Glue DataBrew	26	26	0.981	1
0.995	0.981				
	Grafana	20	20	0.976	1
0.995	0.995				
	GuardDuty	72	132	0.996	1
0.995	0.956				
	IAM	201	334	0.992	0.91
0.99	0.906				
	IAM Role	98	207	0.868	1
0.983	0.845				
	IOT Core	40	54	0.991	1
0.995	0.984				
	Image	74	74	0.994	1
0.995	0.854				
	Image Builder	15	15	0.968	1
0.995	0.995				
	Ingress	15	15	0.969	1
0.995	0.899				
	Inspector Agent	15	15	0.968	1
0.995	0.982				
	Instances	19	38	0.558	1
0.571	0.479				
	Internet	240	345	0.953	1
0.994	0.96				
	Internet Gateway	167	247	0.991	1
0.995	0.907				
	Jenkins	15	30	0.984	1
0.995	0.97				
	Key Management Service	127	155	0.997	1
0.995	0.981				
	Kibana	15	15	0.969	1
0.995	0.995				
	Kinesis Data Streams	150	198	0.997	1
0.995	0.969				
	Kubernetes	15	15	0.968	1
0.995	0.985				
	Lambda	945	2489	0.987	0.991
0.995	0.962				
	Lex	16	16	0.97	1
0.995	0.995				
	MQ	25	57	0.992	1
0.995	0.866				
	Machine Learning	56	56	0.835	1
0.982	0.946				
	Macie	65	146	0.997	1
0.995	0.917				
	Marketplace	21	21	0.98	1
0.995	0.695				
	Memcached	18	36	0.986	1
0.995	0.991				
	Mobile Client	198	249	0.988	0.997
0.995	0.914				

	Mongo DB	26	70	0.873	1
0.995	0.874				
	MySQL	15	15	0.97	1
0.995	0.911				
	NAT Gateway	187	375	0.999	1
0.995	0.955				
	Neptune	42	42	0.985	1
0.995	0.7				
	Network Adapter	15	15	0.968	1
0.995	0.995				
	Network Firewall	15	15	0.969	1
0.995	0.901				
	Notebook	18	18	0.973	1
0.995	0.995				
	Order Controller	18	18	0.974	1
0.995	0.905				
	Organization Trail	32	77	0.994	1
0.995	0.849				
	Parameter Store	26	26	0.982	1
0.995	0.987				
	Pinpoint	16	16	0.97	1
0.995	0.915				
	PostgreSQL	15	15	0.97	1
0.995	0.948				
	Private Link	89	89	0.994	1
0.995	0.941				
	Private Subnet	368	930	0.975	0.981
0.987	0.869				
	Prometheus	20	20	0.976	1
0.995	0.995				
	Public Subnet	338	841	0.998	1
0.995	0.869				
	Quarkus	20	20	0.974	1
0.995	0.982				
	Quicksight	41	51	0.99	1
0.995	0.963				
	RDS	345	685	0.998	1
0.995	0.939				
	React	15	15	0.969	1
0.995	0.867				
	Redis	49	100	0.997	1
0.995	0.965				
	Redshift	73	80	0.994	1
0.995	0.966				
	Region	183	269	0.996	1
0.995	0.902				
	Rekognition	33	33	0.985	1
0.995	0.995				
	Results	17	17	0.565	1
0.626	0.611				
	Route 53	53	53	0.991	1
0.995	0.979				
	Route53	428	611	0.998	1
0.995	0.959				
	S3	977	2096	0.979	0.99
0.995	0.943				
	SAR	18	18	0.974	1
0.995	0.995				
	SDK	123	403	0.978	0.999
0.995	0.954				
	SES	72	87	0.994	1
0.995	0.944				
	SNS	258	279	0.998	1
0.995	0.965				

	SQS	189	199	0.998	1
0.995	0.969				
	SSM Agent	15	15	0.968	1
0.995	0.986				
	Sagemaker	81	267	0.922	0.981
0.987	0.816				
	Secret Manager	46	46	0.988	1
0.995	0.892				
	Security Group	15	15	0.969	1
0.995	0.995				
	Security Hub	31	91	0.995	1
0.995	0.844				
	Server	101	193	0.997	1
0.995	0.953				
	Service Catalog	40	91	0.995	1
0.995	0.911				
	Shield	58	58	0.992	1
0.995	0.993				
	Sign-On	15	15	0.968	1
0.995	0.979				
	Slack	37	37	0.987	1
0.995	0.979				
	Snowball	15	15	0.969	1
0.995	0.995				
	Stack	22	22	0.978	1
0.995	0.938				
	Step Function	32	96	0.995	1
0.995	0.935				
	Storage Gateway	15	15	0.968	1
0.995	0.995				
	SwaggerHub	15	15	0.968	1
0.995	0.995				
	Systems Manager	61	76	0.994	1
0.995	0.983				
	TV	22	22	0.978	1
0.995	0.961				
	Table	88	196	0.997	1
0.995	0.942				
	Task Runner	18	18	0.973	1
0.995	0.995				
	Terraform	32	32	0.985	1
0.995	0.945				
	Text File	54	122	0.943	1
0.994	0.931				
	Textract	17	17	0.972	1
0.995	0.995				
	Transcribe	17	17	0.972	1
0.995	0.995				
	Transfer Family	68	68	0.993	1
0.995	0.984				
	Transit Gateway	35	35	0.986	1
0.995	0.953				
	Translate	49	49	0.99	1
0.995	0.979				
	Trusted Advisor	36	36	0.986	1
0.995	0.983				
	Twilio	15	15	0.968	1
0.995	0.972				
	Users	574	790	0.976	0.989
0.995	0.928				
	VDA	16	16	0.971	1
0.995	0.962				
	VP Gateway	30	36	0.987	1
0.995	0.913				

	VPC Router	50	102	0.991	1
0.995	0.95				
	VPN Connection	21	57	0.991	1
0.995	0.946				
	WAF	112	131	0.996	1
0.995	0.956				
	Web Clients	213	248	0.821	1
0.984	0.89				
	Websites	31	31	0.984	1
0.995	0.959				
	X-Ray	83	95	0.995	1
0.995	0.99				
	aws	971	1219	0.996	0.999
0.995	0.912				
	cache Worker	36	36	0.986	1
0.995	0.968				

Speed: 0.2ms preprocess, 13.9ms inference, 0.0ms loss, 4.2ms postprocess per image

Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100

🚀 Save dir: C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100

✓ best.pt: C:

\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11s_custom_100\weights\best.pt

Ultralytics 8.3.162 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060 Laptop GPU, 8188MiB)

YOLOv1s summary (fused): 100 layers, 9,483,234 parameters, 0 gradients, 21.7 GFLOPs

val: Fast image access (ping: 0.10.0 ms, read: 217.8131.8 MB/s, size: 365.8 KB)

val: Scanning D:\ia4devs\module_05\05_hackaton\data\dataset\aws\test\labels... 1327 images, 0 backgrounds, 0 corrupt: 1

val: New cache created: D:

\ia4devs\module_05\05_hackaton\data\dataset\aws\test\labels.cache

	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100%		166/166 [0:0]				
	all	1327	26828	0.96	0.996	
0.98	0.95					
	ACM	42	42	0.987	1	
0.995	0.995					
	ALB	206	292	0.999	1	
0.995	0.961					
	AMI	24	39	0.986	1	
0.995	0.995					
	API-Gateway	707	1063	0.973	0.997	
0.995	0.973					
Active Directory Service		29	29	0.981	1	
0.995	0.995					
	Airflow_	15	30	0.983	1	
0.995	0.976					
	Amplify	76	76	0.983	1	
0.989	0.868					
Analytics Services		15	15	0.966	1	
0.995	0.979					
	AppFlow	15	15	0.965	1	
0.995	0.995					
	Appsync	50	50	0.994	1	
0.995	0.842					
	Athena	133	141	0.844	1	
0.995	0.956					
	Aurora	79	112	0.993	0.964	
0.979	0.976					
	Auto Scaling	126	211	0.998	1	
0.995	0.942					
Auto Scaling Group		25	58	0.992	1	
0.995	0.957					

	Automated Tests	58	89	0.994	1
0.995	0.962				
	Availability Zone	23	46	0.989	1
0.995	0.993				
	Backup	16	32	0.983	1
0.995	0.995				
	Build Environment	34	34	0.986	1
0.995	0.84				
	CDN	21	21	0.975	1
0.995	0.983				
	CUR	35	35	0.987	1
0.995	0.779				
	Call Metrics	15	15	0.966	1
0.995	0.995				
	Call Recordings	15	15	0.966	1
0.995	0.862				
	Certificate Manager	103	103	0.995	1
0.995	0.995				
	Client	16	61	0.534	0.984
0.663	0.587				
	Cloud Connector	14	28	0.982	1
0.995	0.993				
	Cloud Map	15	15	0.965	1
0.995	0.995				
	Cloud Search	48	48	0.989	1
0.995	0.984				
	Cloud Trail	140	142	0.995	1
0.995	0.991				
	Cloud Watch	468	566	0.999	1
0.995	0.97				
	CloudFormation Stack	124	138	0.996	1
0.995	0.994				
	CloudHSM	33	33	0.984	1
0.995	0.995				
	CloudWatch Alarm	75	106	0.995	1
0.995	0.951				
	Cloudfront	346	366	0.988	0.929
0.992	0.964				
	CodeBuild	140	208	0.997	1
0.995	0.965				
	CodeCommit	52	66	0.992	1
0.995	0.994				
	CodeDeploy	13	13	0.959	1
0.995	0.983				
	CodePipeline	183	190	0.993	1
0.992	0.955				
	Cognito	310	354	0.935	0.887
0.984	0.962				
	Comprehend	73	73	0.992	1
0.995	0.995				
	Config	72	147	0.946	0.98
0.993	0.957				
	Connect	15	15	0.965	1
0.995	0.995				
	Connect Contact Lens	15	15	0.965	1
0.995	0.99				
	Container	86	403	0.999	1
0.995	0.944				
	Control Tower	14	14	0.963	1
0.995	0.995				
	Customer Gateway	35	62	0.991	1
0.995	0.977				
	DSI	31	62	0.992	1
0.995	0.872				

	Data Pipeline	22	22	0.976	1
0.995	0.995				
	DataSync	30	30	1	1
0.995	0.995				
	Deploy Stage	27	27	0.981	1
0.995	0.873				
	Detective	15	15	0.965	1
0.995	0.995				
	Direct Connect	77	112	0.995	0.991
0.995	0.959				
	Distribution	15	15	0.619	1
0.816	0.816				
	Docker Image	44	174	0.99	0.989
0.99	0.838				
	Dynamo DB	619	958	0.967	0.992
0.995	0.969				
	EBS	65	107	1	0.996
0.995	0.938				
	EC2	609	1692	0.983	0.991
0.994	0.965				
	EFS	90	116	0.987	0.983
0.986	0.977				
	EFS Mount Target	95	128	0.998	0.977
0.982	0.964				
	EKS	147	164	0.996	1
0.995	0.98				
	ELB	379	521	0.994	0.964
0.975	0.958				
	EMR	15	15	0.965	1
0.995	0.995				
	Edge Location	15	27	0.982	1
0.995	0.928				
	ElastiCache	101	121	0.995	0.967
0.985	0.968				
Elastic Container Registry		212	212	0.998	1
0.995	0.972				
Elastic Container Service		236	302	0.976	0.937
0.992	0.923				
	Elastic Search	116	117	0.996	1
0.995	0.943				
Elemental MediaConvert		49	64	0.816	1
0.98	0.978				
Elemental MediaPackage		15	15	0.497	1
0.53	0.53				
	Email	29	29	1	0.966
0.982	0.976				
	Endpoint	22	22	0.978	1
0.995	0.982				
	Event Bus	15	15	0.964	1
0.995	0.995				
	EventBridge	41	101	0.995	1
0.995	0.984				
Experiment Duration		14	14	0.516	1
0.572	0.553				
	Experiments	14	14	0.515	1
0.621	0.621				
	Fargate	180	423	0.935	1
0.994	0.958				
Fault Injection Simulator		45	45	0.988	1
0.995	0.963				
	Firewall Manager	15	15	0.965	1
0.995	0.995				
	Flask	17	51	0.989	1
0.995	0.791				

	Flow logs	15	60	0.995	1
0.995	0.915				
	GameLift	15	15	0.967	1
0.995	0.939				
	Git	17	17	0.969	1
0.995	0.96				
	Github	73	90	0.994	1
0.995	0.96				
	Glacier	15	15	0.965	1
0.995	0.995				
	Glue	59	118	0.995	1
0.995	0.965				
	Glue DataBrew	22	22	0.975	1
0.995	0.995				
	Grafana	14	14	0.96	1
0.995	0.995				
	GuardDuty	57	117	0.995	1
0.995	0.978				
	IAM	180	335	0.96	0.934
0.99	0.951				
	IAM Role	78	185	0.855	0.989
0.978	0.895				
	IOT Core	46	52	0.994	1
0.995	0.992				
	Image	63	63	0.992	1
0.995	0.89				
	Image Builder	15	15	0.962	1
0.995	0.995				
	Ingress	17	17	0.969	1
0.995	0.995				
	Inspector Agent	15	15	0.965	1
0.995	0.995				
	Instances	16	32	0.515	1
0.637	0.622				
	Internet	201	272	0.951	0.994
0.994	0.98				
	Internet Gateway	133	200	1	0.999
0.995	0.926				
	Jenkins	15	30	0.982	1
0.995	0.995				
Key Management Service		111	139	0.996	1
0.995	0.995				
	Kibana	18	18	0.971	1
0.995	0.983				
	Kinesis Data Streams	156	207	1	0.988
0.995	0.991				
	Kubernetes	17	17	0.971	1
0.995	0.995				
	Lambda	830	2220	0.988	0.996
0.995	0.978				
	Lex	18	18	0.97	1
0.995	0.995				
	MQ	34	86	0.994	1
0.995	0.963				
	Machine Learning	47	47	0.809	1
0.974	0.969				
	Macie	56	119	0.994	1
0.995	0.966				
	Marketplace	19	19	0.981	1
0.995	0.726				
	Memcached	11	22	0.976	1
0.995	0.983				
	Mobile Client	150	196	1	0.989
0.995	0.921				

	Mongo DB	26	62	0.992	1
0.995	0.92				
	MySQL	15	15	0.967	1
0.995	0.911				
	NAT Gateway	147	293	0.993	0.989
0.995	0.985				
	Neptune	35	35	0.982	1
0.995	0.7				
	Network Adapter	15	15	0.965	1
0.995	0.995				
	Network Firewall	15	15	0.967	1
0.995	0.995				
	Notebook	15	15	0.965	1
0.995	0.995				
	Order Controller	17	17	0.969	1
0.995	0.889				
	Organization Trail	26	71	0.994	1
0.995	0.981				
	Parameter Store	27	27	0.98	1
0.995	0.985				
	Pinpoint	16	16	0.967	1
0.995	0.995				
	PostgreSQL	15	15	0.967	1
0.995	0.987				
	Private Link	87	87	0.994	1
0.995	0.989				
	Private Subnet	335	936	0.994	0.981
0.987	0.927				
	Prometheus	14	14	0.963	1
0.995	0.995				
	Public Subnet	299	715	0.997	0.992
0.995	0.918				
	Quarkus	14	14	0.962	1
0.995	0.995				
	Quicksight	40	50	0.989	1
0.995	0.995				
	RDS	266	551	0.982	0.982
0.982	0.961				
	React	15	15	0.968	1
0.995	0.911				
	Redis	47	98	0.98	1
0.995	0.987				
	Redshift	65	72	0.993	1
0.995	0.993				
	Region	161	243	0.997	1
0.995	0.928				
	Rekognition	37	37	0.985	1
0.995	0.988				
	Results	14	14	0.523	1
0.685	0.685				
	Route 53	39	39	0.962	1
0.989	0.989				
	Route53	376	532	0.995	0.996
0.995	0.974				
	S3	867	1862	0.969	0.982
0.994	0.963				
	SAR	14	14	0.964	1
0.995	0.995				
	SDK	98	301	0.971	1
0.992	0.969				
	SES	69	84	0.994	1
0.995	0.978				
	SNS	232	254	0.998	1
0.995	0.988				

	SQS	184	197	0.997	1
0.995	0.979				
	SSM Agent	15	15	0.965	1
0.995	0.995				
	Sagemaker	76	241	0.991	0.992
0.993	0.823				
	Secret Manager	44	44	0.983	1
0.995	0.995				
	Security Group	16	16	0.967	1
0.995	0.97				
	Security Hub	25	85	0.995	1
0.995	0.953				
	Server	88	165	0.996	1
0.995	0.95				
	Service Catalog	30	72	0.992	1
0.995	0.965				
	Shield	52	52	0.99	1
0.995	0.995				
	Sign-On	15	15	0.965	1
0.995	0.995				
	Slack	30	30	0.982	1
0.995	0.973				
	Snowball	15	15	0.963	1
0.995	0.995				
	Stack	14	14	0.964	1
0.995	0.973				
	Step Function	30	90	0.994	1
0.995	0.922				
	Storage Gateway	15	15	0.965	1
0.995	0.995				
	SwaggerHub	15	15	0.965	1
0.995	0.995				
	Systems Manager	53	68	0.992	1
0.995	0.995				
	TV	12	12	0.959	1
0.995	0.967				
	Table	72	154	0.99	1
0.995	0.954				
	Task Runner	17	17	0.969	1
0.995	0.99				
	Terraform	38	38	0.986	1
0.995	0.97				
	Text File	49	99	0.914	1
0.98	0.955				
	Textract	14	14	0.962	1
0.995	0.995				
	Transcribe	19	19	0.972	1
0.995	0.995				
	Transfer Family	67	67	0.992	1
0.995	0.989				
	Transit Gateway	31	31	0.983	1
0.995	0.962				
	Translate	53	53	0.99	1
0.995	0.995				
	Trusted Advisor	13	13	0.96	1
0.995	0.986				
	Twilio	18	18	0.971	1
0.995	0.995				
	Users	486	656	0.999	0.985
0.995	0.959				
	VDA	14	14	0.964	1
0.995	0.983				
	VP Gateway	27	39	0.987	0.974
0.979	0.934				

	VPC Router	39	80	1	0.994
0.995	0.938				
	VPN Connection	21	48	0.992	1
0.995	0.989				
	WAF	99	109	0.995	1
0.995	0.99				
	Web Clients	202	268	0.831	0.994
0.971	0.909				
	Websites	34	34	0.985	1
0.995	0.993				
	X-Ray	88	112	0.996	1
0.995	0.991				
	aws	845	1067	0.993	0.993
0.995	0.945				
	cache Worker	26	26	0.979	1
0.995	0.995				

Speed: 0.4ms preprocess, 10.0ms inference, 0.0ms loss, 4.4ms postprocess per image

Saving C:\acmattos\dev\tools\Python\ia4devs\runs\detect\val\predictions.json...

Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\val

🎯 Test Metrics (mean per class):

Precision: 0.960
 Recall: 0.996
 mAP@0.5: 0.980
 mAP@0.5:0.95: 0.950

image 1/1 D:\ia4devs\module_05\05_hackaton\data\sample\aws_02.png: 576x640 2 ALBs,
 2 Auto Scalings, 2 Cloud Watchs, 1 Cloudfront, 1 Dynamo DB, 4 EC2s, 1 IAM, 1 NAT
 Gateway,

3 Private Subnets, 3 Public Subnets, 2 RDSS, 1 Region, 1 S3, 1 Users, 2 WAFs, 1 aws,
 209.5ms

Speed: 8.4ms preprocess, 209.5ms inference, 4.7ms postprocess per image at shape (1,
 3, 576, 640)

Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict

1 label saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict\labels

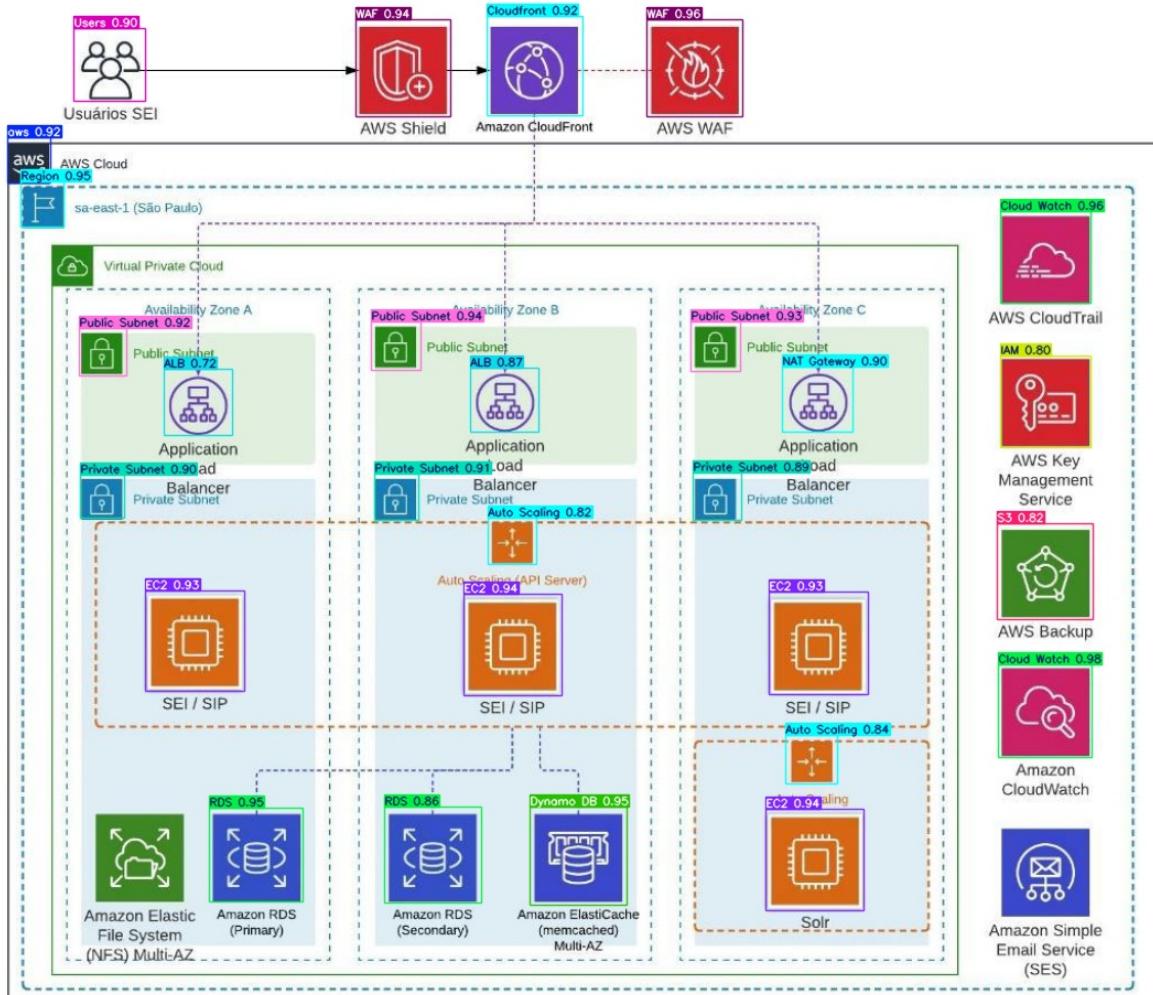
✓ Detailed JSON saved to data\reports\yolo11s_custom_100\results.json

✓ Summary JSON saved to data\reports\yolo11s_custom_100\report.json

[ultralytics.engine.results.Results object with attributes:

```
boxes: ultralytics.engine.results.Boxes object
keypoints: None
masks: None
(...)
obb: None
(...
orig_shape: (993, 1167)
path: 'D:\\ia4devs\\module_05\\05_hackaton\\data\\sample\\aws_02.png'
probs: None
save_dir: 'C:\\acmattos\\dev\\tools\\Python\\ia4devs\\runs\\detect\\predict'
speed: {'preprocess': 8.365600020624697, 'inference': 209.4717000145465,
        'postprocess': 4.683099978137761}]
```

Predição do Modelo do Yolo 11 - S



Detecção do Modelo S

Treinamento do Yolo 11 - Modelo M

Para treinar o modelo, basta ajustar a variável abaixo:

```
yolo: str = 'yolo11m'
```

Depois, execute a chamada a seguir:

```
py model.py
```

Aguardar a conclusão do processo. O treinamento utilizou 82 épocas para treino, gastando 5.280 horas no processo. O mecanismo de Early Stop foi acionado após 10 épocas que passarem sem nenhum progresso no treinamento do modelo. Um exemplo de log de execução pode ser visto abaixo:

```

New https://pypi.org/project/ultralytics/8.3.162 available Update with 'pip install
    -U ultralytics'
Ultralytics 8.3.161 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060
    Laptop GPU, 8188MiB)
engine\trainer: agnostic_nms=False, amp=True, augment=True, auto_augment=randaugment,
    batch=6,
bgr=0.0, box=7.5, cache=False, cfg=None, classes=None, close_mosaic=10, cls=0.5,
    conf=None,
copy_paste=0.0, copy_paste_mode=flip, cos_lr=False, cutmix=0.0, data=./data/dataset/
    aws/data.yaml,
degrees=0.0, deterministic=True, device=0, dfl=1.5, dnn=False, dropout=0.0, dynamic=False,
embed=None, epochs=100, erasing=0.4, exist_ok=False, fliplr=0.5, flipud=0.0, format=torchscript,
fraction=1.0, freeze=None, half=False, hsv_h=0.015, hsv_s=0.7, hsv_v=0.4, imgsz=640,
    int8=False,
iou=0.7, keras=False, kobj=1.0, line_width=None, lr0=0.0005, lrf=0.05, mask_ratio=4,
    max_det=300,
mixup=0.5, mode=train, model=./data/model/yolo11m.pt, momentum=0.937, mosaic=1.0,
    multi_scale=True,
name=yolo11m_custom_100, nbs=64, nms=False, opset=None, optimize=False, optimizer=AdamW,
overlap_mask=True, patience=10, perspective=0.0, plots=True, pose=12.0, pretrained=True,
profile=False, project=None, rect=False, resume=False, retina_masks=False, save=True,
save_conf=False, save_crop=False,
save_dir=C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100,
    save_frames=False,
save_json=False, save_period=-1, save_txt=False, scale=0.5, seed=0, shear=0.0, show=False,
show_boxes=True, show_conf=True, show_labels=True, simplify=True, single_cls=False,
    source=None,
split=val, stream_buffer=False, task=detect, time=None, tracker=botsort.yaml,
    translate=0.1,
val=True, verbose=True, vid_stride=1, visualize=False, warmup_bias_lr=0.1,
    warmup_epochs=3,
warmup_momentum=0.8, weight_decay=0.0005, workers=8, workspace=None
Overriding model.yaml nc=80 with nc=182

```

	from	n	params	module	arguments
0	-1	1	1856	ultralytics.nn.modules.conv.Conv	[3, 64, 3, 2]
1	-1	1	73984	ultralytics.nn.modules.conv.Conv	[64, 128, 3, 2]
2	-1	1	111872	ultralytics.nn.modules.block.C3k2	[128, 256, 1,
	True,	0.25]			
3	-1	1	590336	ultralytics.nn.modules.conv.Conv	[256, 256, 3, 2]
4	-1	1	444928	ultralytics.nn.modules.block.C3k2	[256, 512, 1,
	True,	0.25]			
5	-1	1	2360320	ultralytics.nn.modules.conv.Conv	[512, 512, 3, 2]
6	-1	1	1380352	ultralytics.nn.modules.block.C3k2	[512, 512, 1,
	True]				
7	-1	1	2360320	ultralytics.nn.modules.conv.Conv	[512, 512, 3, 2]
8	-1	1	1380352	ultralytics.nn.modules.block.C3k2	[512, 512, 1,
	True]				
9	-1	1	656896	ultralytics.nn.modules.block.SPPF	[512, 512, 5]
10	-1	1	990976	ultralytics.nn.modules.block.C2PSA	[512, 512, 1]
11	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2,
	'nearest']			
12	[-1, 6]	1	0	ultralytics.nn.modules.conv.Concat	[1]
13	-1	1	1642496	ultralytics.nn.modules.block.C3k2	[1024, 512, 1,
	True]				
14	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2,
	'nearest']			
15	[-1, 4]	1	0	ultralytics.nn.modules.conv.Concat	[1]
16	-1	1	542720	ultralytics.nn.modules.block.C3k2	[1024, 256, 1,
	True]				
17	-1	1	590336	ultralytics.nn.modules.conv.Conv	[256, 256, 3, 2]
18	[-1, 13]	1	0	ultralytics.nn.modules.conv.Concat	[1]

```

19      -1 1 1511424 ultralytics.nn.modules.block.C3k2 [768, 512, 1,
    True]
20      -1 1 2360320 ultralytics.nn.modules.conv.Conv [512, 512, 3, 2]
21 [-1, 10] 1 0 ultralytics.nn.modules.conv.Concat [1]
22      -1 1 1642496 ultralytics.nn.modules.block.C3k2 [1024, 512, 1,
    True]
23 [16, 19, 22] 1 1551346 ultralytics.nn.modules.head.Detect [182, [256, 512,
512]]
YOLO11m summary: 231 layers, 20,193,330 parameters, 20,193,314 gradients, 69.0 GFLOPs

Transferred 643/649 items from pretrained weights
ClearML Task: created new task id=4d88d8495b224537b71cc9f78d532fad
ClearML results page: https://app.clear.ml/projects/14f0119248fa451f826c387955b212a3/
experiments/4d88d8495b224537b71cc9f78d532fad/output/log
WARNING ClearML Initialized a new task. If you want to run remotely, please add
clearml-init and connect your arguments before initializing YOLO.
Freezing layer 'model.23.dfl.conv.weight'
AMP: running Automatic Mixed Precision (AMP) checks...
AMP: checks passed
train: Fast image access (ping: 0.20.1 ms, read: 900.8340.6 MB/s, size: 1118.3 KB)
train: Scanning D:
    \ia4devs\module_05\05_hackaton\data\dataset\aws\train\labels.cache... 3457
    images, 0 backgrounds, 0 c
albumentations: Blur(p=0.01, blur_limit=(3, 7)), MedianBlur(p=0.01, blur_limit=(3,
7)), ToGray(p=0.01, method='weighted_average', num_output_channels=3), CLAHE(p=0.01,
clip_limit=(1.0, 4.0), tile_grid_size=(8, 8))
val: Fast image access (ping: 0.10.1 ms, read: 432.2297.8 MB/s, size: 607.4 KB)
val: Scanning D:\ia4devs\module_05\05_hackaton\data\dataset\aws\valid\labels.cache...
    1488 images, 0 backgrounds, 0 cor
Plotting labels to C:
    \acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100\labels.jpg...

optimizer: AdamW(lr=0.0005, momentum=0.937) with parameter groups 106
    weight(decay=0.0), 113 weight(decay=0.000515625), 112 bias(decay=0.0)
Image sizes 640 train, 640 val
Using 8 dataloader workers
Logging results to C:
    \acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100
Starting training for 100 epochs...



| Epoch | GPU_mem                            | box_loss   | cls_loss        | dfl_loss     | Instances | Size                 |
|-------|------------------------------------|------------|-----------------|--------------|-----------|----------------------|
| 1/100 | 7.376                              | 1.421      | 5.513           | 1.155        | 253       | 384: 2%              |
|       | ██████████   10/577 [00:04<03:27,  |            |                 |              |           |                      |
| 1/100 | 7.556                              | 1.108      | 2.564           | 0.9695       | 242       | 576: 67% ██████████  |
|       | ██████████   388/577 [02:18<00:49, |            |                 |              |           |                      |
| 1/100 | 7.556                              | 1.071      | 2.245           | 0.9587       | 29        | 544: 100% ██████████ |
|       | ██████████   577/577 [03:18<00:00, |            |                 |              |           |                      |
|       |                                    | Class      | Images          | Box(P)       | R         | mAP50                |
|       |                                    | mAP50-95): | 7% █████        | 9/124 [00:01 |           |                      |
|       |                                    | Class      | Images          | Box(P)       | R         | mAP50                |
|       |                                    | mAP50-95): | 100% ██████████ | 124/124 [00: |           |                      |
|       |                                    | all        | 1488            | 30084        | 0.695     | 0.418                |
|       |                                    |            |                 |              |           | 0.493                |
|       |                                    |            |                 |              |           | 0.376                |



| Epoch | GPU_mem                            | box_loss   | cls_loss        | dfl_loss     | Instances | Size                 |
|-------|------------------------------------|------------|-----------------|--------------|-----------|----------------------|
| 2/100 | 7.546                              | 0.9569     | 1.188           | 0.9321       | 25        | 672: 100% ██████████ |
|       | ██████████   577/577 [02:54<00:00, |            |                 |              |           |                      |
|       |                                    | Class      | Images          | Box(P)       | R         | mAP50                |
|       |                                    | mAP50-95): | 100% ██████████ | 124/124 [00: |           |                      |
|       |                                    | all        | 1488            | 30084        | 0.754     | 0.715                |
|       |                                    |            |                 |              |           | 0.794                |
|       |                                    |            |                 |              |           | 0.612                |



| Epoch | GPU_mem | box_loss | cls_loss | dfl_loss | Instances | Size |
|-------|---------|----------|----------|----------|-----------|------|
|-------|---------|----------|----------|----------|-----------|------|


```

3/100	7.86G	0.9032	0.9137	0.9158	9	672: 100%
	██████████ 577/577 [02:38<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						
	all	1488	30084	0.842	0.836	0.915
	0.727					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
4/100	7.69G	0.8737	0.8256	0.9097	12	736: 100%
	██████████ 577/577 [03:48<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						
	all	1488	30084	0.863	0.886	0.939
	0.764					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
5/100	7.72G	0.8313	0.7116	0.9021	24	896: 100%
	██████████ 577/577 [04:20<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						
	all	1488	30084	0.899	0.929	0.969
	0.803					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
6/100	7.78G	0.7875	0.6362	0.8858	80	768: 100%
	██████████ 577/577 [04:44<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						
	all	1488	30084	0.945	0.962	0.978
	0.836					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
7/100	7.69G	0.7651	0.6092	0.8865	27	960: 100%
	██████████ 577/577 [03:57<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						
	all	1488	30084	0.928	0.977	0.98
	0.853					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
8/100	7.64G	0.73	0.556	0.8752	16	864: 100%
	██████████ 577/577 [02:39<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						
	all	1488	30084	0.932	0.98	0.98
	0.85					
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
9/100	7.76G	0.7183	0.5498	0.8703	29	640: 100%
	██████████ 577/577 [02:51<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						
	all	1488	30084	0.955	0.976	0.982
	0.872					
(...)						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
49/100	7.66G	0.4436	0.3047	0.8118	52	608: 100%
	██████████ 577/577 [03:15<00:00,					
	Class	Images	Instances	Box(P)	R	mAP50
mAP50-95): 100% ██████████ 124/124 [00:						

```
          all      1488    30084    0.951    0.999    0.984
0.948

Epoch   GPU_mem   box_loss   cls_loss   dfl_loss   Instances   Size
50/100   7.56G    0.4367    0.3027    0.8113     32        928: 100%
[██████████| 577/577 [04:10<00:00,
Class   Images   Instances   Box(P)      R       mAP50
mAP50-95): 100%|██████████| 124/124 [00:
          all      1488    30084    0.971    0.99     0.982
0.947

Epoch   GPU_mem   box_loss   cls_loss   dfl_loss   Instances   Size
51/100   7.54G    0.438     0.303     0.8122     54        736: 100%
[██████████| 577/577 [03:39<00:00,
Class   Images   Instances   Box(P)      R       mAP50
mAP50-95): 100%|██████████| 124/124 [00:
          all      1488    30084    0.959    0.993    0.983
0.948

Epoch   GPU_mem   box_loss   cls_loss   dfl_loss   Instances   Size
52/100   7.87G    0.4401    0.3049    0.8098     48        864: 100%
[██████████| 577/577 [02:46<00:00,
Class   Images   Instances   Box(P)      R       mAP50
mAP50-95): 100%|██████████| 124/124 [00:
          all      1488    30084    0.958    0.994    0.984
0.949

(...)

Epoch   GPU_mem   box_loss   cls_loss   dfl_loss   Instances   Size
81/100   7.8G     0.3734    0.2554    0.799      68        320: 100%
[██████████| 577/577 [04:41<00:00,
Class   Images   Instances   Box(P)      R       mAP50
mAP50-95): 100%|██████████| 124/124 [00:
          all      1488    30084    0.959    0.997    0.982
0.956

Epoch   GPU_mem   box_loss   cls_loss   dfl_loss   Instances   Size
82/100   8.03G    0.3781    0.2593    0.7981     21        320: 100%
[██████████| 577/577 [02:51<00:00,
Class   Images   Instances   Box(P)      R       mAP50
mAP50-95): 100%|██████████| 124/124 [00:
          all      1488    30084    0.955    0.998    0.982
0.957

EarlyStopping: Training stopped early as no improvement observed in last 10 epochs.
Best results observed at epoch 72, best model saved as best.pt.
To update EarlyStopping(patience=10) pass a new patience value, i.e. `patience=300`  

or use `patience=0` to disable EarlyStopping.

82 epochs completed in 5.280 hours.
Optimizer stripped from C:
\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100\weights\last.pt,
40.8MB

Optimizer stripped from C:
\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100\weights\best.pt,
40.8MB

Validating C:
\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100\weights\best.pt...
```

Ultralytics 8.3.161 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060 Laptop GPU, 8188MiB)							
YOLOv11m summary (fused): 125 layers, 20,170,354 parameters, 0 gradients, 68.4 GFLOPs							
	Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
	██████████ 124/124 [00:						
	all	1488	30084	0.955	0.995	0.984	0.936
	ACM	62	62	0.99	1	0.995	0.953
	ALB	228	332	0.998	1	0.995	0.947
	AMI	29	44	0.986	1	0.995	0.979
	API-Gateway	774	1178	0.968	1	0.995	0.958
Active Directory Service		31	31	0.981	1	0.995	0.978
Airflow_		15	30	0.98	1	0.995	0.984
Amplify		84	84	0.993	1	0.995	0.895
Analytics Services		15	15	0.962	1	0.995	0.988
AppFlow		15	15	0.961	1	0.995	0.995
Appsync		61	61	0.991	1	0.995	0.826
Athena		143	148	0.84	1	0.99	0.965
Aurora		89	126	0.995	1	0.995	0.982
Auto Scaling		173	307	0.995	1	0.995	0.929
Auto Scaling Group		35	88	0.993	1	0.995	0.841
Automated Tests		64	98	0.994	1	0.995	0.974
Availability Zone		24	48	0.987	1	0.995	0.956
Backup		15	30	0.98	1	0.995	0.995
Build Environment		44	44	0.975	1	0.995	0.868
CDN		20	20	0.884	1	0.995	0.975
CUR		42	42	0.987	1	0.995	0.801
Call Metrics		15	15	0.961	1	0.995	0.963
Call Recordings		15	15	0.961	1	0.995	0.91
Certificate Manager		98	98	0.994	1	0.995	0.988
Client		16	61	0.669	1	0.742	0.667
Cloud Connector		16	32	0.981	1	0.995	0.94
Cloud Map		15	15	0.961	1	0.995	0.995
Cloud Search		56	56	0.989	1	0.995	0.96
Cloud Trail		187	192	0.996	1	0.995	0.972
Cloud Watch		543	644	0.999	1	0.995	0.949
CloudFormation Stack		150	168	0.994	1	0.995	0.961
CloudHSM		34	34	0.982	1	0.995	0.916
CloudWatch Alarm		87	121	0.995	1	0.995	0.942
Cloudfront		401	427	0.926	0.995	0.995	0.962
CodeBuild		157	245	0.998	1	0.995	0.961
CodeCommit		68	80	0.992	1	0.995	0.979
CodeDeploy		17	17	0.965	1	0.995	0.995
CodePipeline		214	220	0.861	1	0.995	0.934
Cognito		346	391	0.846	1	0.984	0.952
Comprehend		72	72	0.991	1	0.995	0.994
Config		103	178	0.982	0.92	0.991	0.903
Connect		15	15	1	1	0.995	0.995
Connect Contact Lens		15	15	0.961	1	0.995	0.987
Container		79	346	0.984	1	0.995	0.903
Control Tower		17	17	0.965	1	0.995	0.995
Customer Gateway		38	74	0.992	1	0.995	0.965
DSI		34	68	0.991	1	0.995	0.884
Data Pipeline		23	23	0.973	1	0.995	0.928
DataSync		32	32	0.981	1	0.995	0.991
Deploy Stage		30	30	0.98	1	0.995	0.924
Detective		15	15	0.961	1	0.995	0.915
Direct Connect		91	126	0.995	1	0.995	0.958
Distribution		15	15	0.609	1	0.895	0.887
Docker Image		56	179	0.912	1	0.995	0.836
Dynamo DB		660	979	0.957	1	0.995	0.964
EBS		92	147	0.996	1	0.995	0.953
EC2		707	1935	0.986	1	0.995	0.936

	EFS	100	133	0.995	1	0.995	0.945
EFS Mount Target	99	129	0.995	1	0.995	0.958	
	EKS	161	184	0.997	1	0.995	0.977
	ELB	425	583	0.994	0.969	0.975	0.944
	EMR	15	15	0.961	1	0.995	0.895
Edge Location	20	42	0.985	1	0.995	0.982	
	ElastiCache	138	170	0.996	1	0.995	0.954
Elastic Container Registry	235	235	0.997	1	0.995	0.958	
Elastic Container Service	258	331	0.909	1	0.994	0.901	
	Elastic Search	142	147	0.996	1	0.995	0.948
Elemental MediaConvert	49	66	0.952	0.788	0.965	0.951	
Elemental MediaPackage	15	15	0.462	1	0.605	0.605	
	Email	25	25	0.977	1	0.995	0.987
	Endpoint	27	27	0.979	1	0.995	0.927
	Event Bus	16	16	0.963	1	0.995	0.995
	EventBridge	60	120	0.971	1	0.995	0.881
Experiment Duration	17	17	0.56	1	0.612	0.588	
	Experiments	17	17	0.559	1	0.675	0.675
	Fargate	193	427	0.981	1	0.995	0.925
Fault Injection Simulator	49	49	0.988	1	0.995	0.919	
	Firewall Manager	15	15	1	1	0.995	0.914
	Flask	15	45	0.964	1	0.995	0.868
	Flow logs	15	60	0.99	1	0.995	0.848
	GameLift	17	17	0.966	1	0.995	0.924
	Git	15	15	0.961	1	0.995	0.968
	Github	81	95	0.993	1	0.995	0.962
	Glacier	15	15	1	1	0.995	0.978
	Glue	58	116	0.993	1	0.995	0.933
	Glue DataBrew	26	26	0.977	1	0.995	0.995
	Grafana	20	20	1	1	0.995	0.995
	GuardDuty	72	132	0.995	1	0.995	0.928
	IAM	201	334	0.894	1	0.991	0.9
	IAM Role	98	207	0.872	1	0.98	0.836
	IOT Core	40	54	0.989	1	0.995	0.978
	Image	74	74	0.992	1	0.995	0.876
	Image Builder	15	15	0.961	1	0.995	0.995
	Ingress	15	15	0.961	1	0.995	0.985
Inspector Agent	15	15	0.961	1	0.995	0.878	
	Instances	19	38	0.57	0.488	0.651	0.561
	Internet	240	345	1	0.965	0.994	0.963
Internet Gateway	167	247	0.998	1	0.995	0.936	
	Jenkins	15	30	0.98	1	0.995	0.945
Key Management Service	127	155	0.996	1	0.995	0.99	
	Kibana	15	15	0.962	1	0.995	0.923
Kinesis Data Streams	150	198	0.996	1	0.995	0.968	
	Kubernetes	15	15	0.962	1	0.995	0.96
	Lambda	945	2489	0.948	1	0.995	0.954
	Lex	16	16	0.963	1	0.995	0.995
	MQ	25	57	0.99	1	0.995	0.916
Machine Learning	56	56	0.829	1	0.982	0.923	
	Macie	65	146	0.996	1	0.995	0.95
	Marketplace	21	21	0.974	1	0.995	0.634
	Memcached	18	36	0.983	1	0.995	0.98
Mobile Client	198	249	0.985	1	0.995	0.93	
	Mongo DB	26	70	0.929	1	0.995	0.904
	MySQL	15	15	0.961	1	0.995	0.99
NAT Gateway	187	375	0.998	1	0.995	0.962	
	Neptune	42	42	0.6	1	0.995	0.764
Network Adapter	15	15	0.961	1	0.995	0.995	
Network Firewall	15	15	0.961	1	0.995	0.961	
	Notebook	18	18	0.967	1	0.995	0.995
Order Controller	18	18	0.967	1	0.995	0.989	

Organization Trail	32	77	0.992	1	0.995	0.854
Parameter Store	26	26	0.977	1	0.995	0.995
Pinpoint	16	16	0.963	1	0.995	0.995
PostgreSQL	15	15	0.961	1	0.995	0.986
Private Link	89	89	0.985	1	0.995	0.949
Private Subnet	368	930	0.973	0.982	0.986	0.864
Prometheus	20	20	0.969	1	0.995	0.995
Public Subnet	338	841	0.995	1	0.995	0.865
Quarkus	20	20	0.97	1	0.995	0.984
Quicksight	41	51	0.988	1	0.995	0.986
RDS	345	685	0.999	1	0.995	0.95
React	15	15	0.961	1	0.995	0.814
Redis	49	100	0.994	1	0.995	0.975
Redshift	73	80	0.992	1	0.995	0.951
Region	183	269	0.997	1	0.995	0.879
Rekognition	33	33	0.982	1	0.995	0.992
Results	17	17	0.558	1	0.901	0.901
Route 53	53	53	0.989	1	0.995	0.995
Route53	428	611	0.999	1	0.995	0.957
S3	977	2096	0.94	1	0.995	0.943
SAR	18	18	1	1	0.995	0.995
SDK	123	403	1	0.975	0.995	0.965
SES	72	87	0.992	1	0.995	0.951
SNS	258	279	0.998	1	0.995	0.977
SQS	189	199	0.997	1	0.995	0.968
SSM Agent	15	15	0.961	1	0.995	0.865
Sagemaker	81	267	0.718	1	0.968	0.809
Secret Manager	46	46	0.987	1	0.995	0.926
Security Group	15	15	1	1	0.995	0.995
Security Hub	31	91	0.994	1	0.995	0.895
Server	101	193	0.997	1	0.995	0.953
Service Catalog	40	91	0.993	1	0.995	0.936
Shield	58	58	0.99	1	0.995	0.994
Sign-On	15	15	0.96	1	0.995	0.995
Slack	37	37	0.984	1	0.995	0.979
Snowball	15	15	0.961	1	0.995	0.995
Stack	22	22	0.973	1	0.995	0.901
Step Function	32	96	0.994	1	0.995	0.914
Storage Gateway	15	15	0.961	1	0.995	0.995
SwaggerHub	15	15	0.961	1	0.995	0.995
Systems Manager	61	76	0.992	1	0.995	0.956
TV	22	22	0.974	1	0.995	0.936
Table	88	196	0.997	1	0.995	0.957
Task Runner	18	18	0.968	1	0.995	0.986
Terraform	32	32	0.981	1	0.995	0.935
Text File	54	122	0.943	1	0.994	0.964
Textract	17	17	0.965	1	0.995	0.995
Transcribe	17	17	0.965	1	0.995	0.995
Transfer Family	68	68	0.991	1	0.995	0.976
Transit Gateway	35	35	0.983	1	0.995	0.978
Translate	49	49	0.987	1	0.995	0.99
Trusted Advisor	36	36	0.983	1	0.995	0.995
Twilio	15	15	0.961	1	0.995	0.995
Users	574	790	0.994	0.996	0.995	0.922
VDA	16	16	0.964	1	0.995	0.964
VP Gateway	30	36	0.984	1	0.995	0.959
VPC Router	50	102	0.994	1	0.995	0.962
VPN Connection	21	57	0.989	1	0.995	0.984
WAF	112	131	0.995	1	0.995	0.962
Web Clients	213	248	0.82	1	0.984	0.904
Websites	31	31	0.98	1	0.995	0.956
X-Ray	83	95	0.972	1	0.995	0.968

aws	971	1219	0.997	1	0.995	0.899
cache Worker	36	36	0.983	1	0.995	0.995
Speed: 0.2ms preprocess, 12.1ms inference, 0.0ms loss, 1.0ms postprocess per image						
Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100						
🚀 Save dir: C:\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100						
✓ best.pt: C:						
\acmattos\dev\tools\Python\ia4devs\runs\detect\yolo11m_custom_100\weights\best.pt						
Ultralytics 8.3.161 Python-3.12.6 torch-2.7.1+cu128 CUDA:0 (NVIDIA GeForce RTX 4060 Laptop GPU, 8188MiB)						
YOLOv11m summary (fused): 125 layers, 20,170,354 parameters, 0 gradients, 68.4 GFLOPs						
val: Fast image access (ping: 0.00.0 ms, read: 713.9422.1 MB/s, size: 628.8 KB)						
val: Scanning D:\ia4devs\module_05\05_hackaton\data\dataset\aws\test\labels.cache...						
1327 images, 0 backgrounds, 0 corr						
Class Images Instances Box(P R mAP50 mAP50-95): 100%						
███████████ 166/166 [00:						
all 1327 26828 0.958 0.989 0.98 0.957: 100%						
███████████ 166/166 [00:						
ACM	42	42	0.985	1	0.995	0.995
ALB	206	292	1	0.989	0.995	0.96
AMI	24	39	0.984	1	0.995	0.995
API-Gateway	707	1063	0.973	1	0.995	0.98
Active Directory Service	29	29	0.98	1	0.995	0.995
Airflow_	15	30	0.98	1	0.995	0.988
Amplify	76	76	0.994	1	0.995	0.925
Analytics Services	15	15	0.961	1	0.995	0.995
AppFlow	15	15	0.96	1	0.995	0.995
Appsync	50	50	0.989	1	0.995	0.857
Athena	133	141	0.914	1	0.995	0.979
Aurora	79	112	0.994	0.964	0.978	0.975
Auto Scaling	126	211	0.999	1	0.995	0.949
Auto Scaling Group	25	58	0.99	1	0.995	0.931
Automated Tests	58	89	0.993	1	0.995	0.974
Availability Zone	23	46	0.987	1	0.995	0.995
Backup	16	32	0.981	1	0.995	0.995
Build Environment	34	34	0.979	1	0.995	0.852
CDN	21	21	0.971	1	0.995	0.983
CUR	35	35	0.984	1	0.995	0.865
Call Metrics	15	15	0.961	1	0.995	0.995
Call Recordings	15	15	0.961	1	0.995	0.921
Certificate Manager	103	103	0.994	1	0.995	0.995
Client	16	61	0.5	1	0.616	0.562
Cloud Connector	14	28	0.978	1	0.995	0.974
Cloud Map	15	15	0.908	1	0.995	0.995
Cloud Search	48	48	0.987	1	0.995	0.993
Cloud Trail	140	142	0.995	1	0.995	0.988
Cloud Watch	468	566	0.999	1	0.995	0.972
CloudFormation Stack	124	138	0.995	1	0.995	0.994
CloudHSM	33	33	0.981	1	0.995	0.995
CloudWatch Alarm	75	106	0.994	1	0.995	0.954
Cloudfront	346	366	0.941	1	0.995	0.975
CodeBuild	140	208	0.997	1	0.995	0.978
CodeCommit	52	66	0.991	1	0.995	0.994
CodeDeploy	13	13	0.949	1	0.995	0.99
CodePipeline	183	190	0.851	1	0.992	0.956
Cognito	310	354	0.893	0.992	0.989	0.977
Comprehend	73	73	0.992	1	0.995	0.995
Config	72	147	0.995	0.898	0.99	0.966
Connect	15	15	1	1	0.995	0.995
Connect Contact Lens	15	15	0.961	1	0.995	0.995
Container	86	403	0.994	1	0.995	0.95
Control Tower	14	14	0.958	1	0.995	0.995

Customer Gateway	35	62	0.99	1	0.995	0.974
DSI	31	62	0.991	1	0.995	0.888
Data Pipeline	22	22	0.972	1	0.995	0.995
DataSync	30	30	1	1	0.995	0.995
Deploy Stage	27	27	0.978	1	0.995	0.873
Detective	15	15	0.961	1	0.995	0.995
Direct Connect	77	112	0.994	0.991	0.995	0.972
Distribution	15	15	0.855	0.333	0.888	0.888
Docker Image	44	174	0.977	0.983	0.989	0.891
Dynamo DB	619	958	0.976	0.992	0.995	0.971
EBS	65	107	0.995	0.991	0.995	0.95
EC2	609	1692	0.982	0.994	0.994	0.967
EFS	90	116	0.991	0.971	0.988	0.983
EFS Mount Target	95	128	1	0.974	0.984	0.971
EKS	147	164	0.995	1	0.995	0.981
ELB	379	521	0.981	0.964	0.975	0.96
EMR	15	15	1	1	0.995	0.995
Edge Location	15	27	0.977	1	0.995	0.967
ElastiCache	101	121	0.993	0.983	0.99	0.978
Elastic Container Registry	212	212	0.998	1	0.995	0.98
Elastic Container Service	236	302	0.918	1	0.995	0.937
Elastic Search	116	117	0.995	1	0.995	0.962
Elemental MediaConvert	49	64	0.965	0.797	0.965	0.965
Elemental MediaPackage	15	15	0.493	1	0.568	0.568
Email	29	29	1	0.987	0.995	0.986
Endpoint	22	22	0.974	1	0.995	0.942
Event Bus	15	15	0.96	1	0.995	0.995
EventBridge	41	101	0.994	1	0.995	0.992
Experiment Duration	14	14	0.512	1	0.642	0.634
Experiments	14	14	0.511	1	0.647	0.647
Fargate	180	423	0.992	1	0.995	0.964
Fault Injection Simulator	45	45	0.987	1	0.995	0.957
Firewall Manager	15	15	0.962	1	0.995	0.995
Flask	17	51	0.985	1	0.995	0.882
Flow logs	15	60	0.99	1	0.995	0.946
GameLift	15	15	0.959	1	0.995	0.941
Git	17	17	0.965	1	0.995	0.939
Github	73	90	0.993	1	0.995	0.98
Glacier	15	15	1	1	0.995	0.995
Glue	59	118	0.995	1	0.995	0.967
Glue DataBrew	22	22	0.973	1	0.995	0.995
Grafana	14	14	0.958	1	0.995	0.995
GuardDuty	57	117	0.995	1	0.995	0.984
IAM	180	335	0.911	0.997	0.991	0.967
IAM Role	78	185	0.86	1	0.984	0.903
IOT Core	46	52	1	0.994	0.995	0.995
Image	63	63	0.991	1	0.995	0.914
Image Builder	15	15	0.956	1	0.995	0.995
Ingress	17	17	0.965	1	0.995	0.995
Inspector Agent	15	15	0.961	1	0.995	0.995
Instances	16	32	0.515	0.438	0.589	0.584
Internet	201	272	0.992	0.945	0.993	0.975
Internet Gateway	133	200	0.992	1	0.995	0.942
Jenkins	15	30	0.979	1	0.995	0.995
Key Management Service	111	139	0.995	1	0.995	0.994
Kibana	18	18	0.967	1	0.995	0.932
Kinesis Data Streams	156	207	1	0.989	0.995	0.99
Kubernetes	17	17	0.967	1	0.995	0.995
Lambda	830	2220	0.974	1	0.995	0.982
Lex	18	18	0.967	1	0.995	0.995
MQ	34	86	0.993	1	0.995	0.974
Machine Learning	47	47	0.803	1	0.979	0.976

Macie	56	119	0.995	1	0.995	0.985
Marketplace	19	19	0.972	1	0.995	0.689
Memcached	11	22	0.973	1	0.995	0.967
Mobile Client	150	196	0.995	0.996	0.995	0.942
Mongo DB	26	62	0.99	1	0.995	0.903
MySQL	15	15	0.961	1	0.995	0.986
NAT Gateway	147	293	0.999	0.99	0.995	0.988
Neptune	35	35	0.973	1	0.995	0.755
Network Adapter	15	15	0.96	1	0.995	0.995
Network Firewall	15	15	1	1	0.995	0.995
Notebook	15	15	0.961	1	0.995	0.995
Order Controller	17	17	0.924	1	0.995	0.995
Organization Trail	26	71	0.992	1	0.995	0.977
Parameter Store	27	27	0.978	1	0.995	0.995
Pinpoint	16	16	0.963	1	0.995	0.995
PostgreSQL	15	15	0.961	1	0.995	0.957
Private Link	87	87	0.983	1	0.995	0.995
Private Subnet	335	936	0.983	0.981	0.987	0.926
Prometheus	14	14	0.958	1	0.995	0.995
Public Subnet	299	715	0.999	0.992	0.995	0.925
Quarkus	14	14	0.958	1	0.995	0.995
Quicksight	40	50	0.988	1	0.995	0.995
RDS	266	551	0.984	0.985	0.984	0.967
React	15	15	0.961	1	0.995	0.96
Redis	47	98	1	0.996	0.995	0.989
Redshift	65	72	0.991	1	0.995	0.995
Region	161	243	0.997	1	0.995	0.931
Rekognition	37	37	0.984	1	0.995	0.995
Results	14	14	0.509	1	0.572	0.572
Route 53	39	39	0.96	1	0.995	0.995
Route53	376	532	0.997	0.998	0.995	0.979
S3	867	1862	0.957	0.991	0.994	0.971
SAR	14	14	0.957	1	0.995	0.995
SDK	98	301	0.991	0.963	0.993	0.976
SES	69	84	0.993	0.988	0.994	0.988
SNS	232	254	0.999	1	0.995	0.99
SQS	184	197	0.997	1	0.995	0.981
SSM Agent	15	15	0.961	1	0.995	0.995
Sagemaker	76	241	0.746	0.986	0.951	0.819
Secret Manager	44	44	0.986	1	0.995	0.995
Security Group	16	16	0.963	1	0.995	0.985
Security Hub	25	85	0.994	1	0.995	0.989
Server	88	165	0.996	1	0.995	0.952
Service Catalog	30	72	0.992	1	0.995	0.977
Shield	52	52	0.988	1	0.995	0.995
Sign-On	15	15	0.96	1	0.995	0.995
Slack	30	30	0.98	1	0.995	0.995
Snowball	15	15	0.961	1	0.995	0.995
Stack	14	14	1	1	0.995	0.991
Step Function	30	90	0.993	1	0.995	0.926
Storage Gateway	15	15	0.96	1	0.995	0.995
SwaggerHub	15	15	0.96	1	0.995	0.995
Systems Manager	53	68	0.991	1	0.995	0.995
TV	12	12	0.957	1	0.995	0.97
Table	72	154	0.993	1	0.995	0.952
Task Runner	17	17	1	1	0.995	0.995
Terraform	38	38	0.984	1	0.995	0.994
Text File	49	99	0.913	1	0.975	0.965
Textract	14	14	0.957	1	0.995	0.995
Transcribe	19	19	0.968	1	0.995	0.995
Transfer Family	67	67	0.991	1	0.995	0.988
Transit Gateway	31	31	0.96	1	0.995	0.992

Translate	53	53	0.988	1	0.995	0.995
Trusted Advisor	13	13	0.956	1	0.995	0.99
Twilio	18	18	0.967	1	0.995	0.995
Users	486	656	0.999	0.991	0.995	0.96
VDA	14	14	0.958	1	0.995	0.995
VP Gateway	27	39	1	0.992	0.995	0.957
VPC Router	39	80	0.992	1	0.995	0.962
VPN Connection	21	48	0.989	1	0.995	0.993
WAF	99	109	0.994	1	0.995	0.992
Web Clients	202	268	0.83	1	0.973	0.917
Websites	34	34	0.981	1	0.995	0.995
X-Ray	88	112	0.992	1	0.995	0.994
aws	845	1067	0.991	0.998	0.994	0.94
cache Worker	26	26	0.977	1	0.995	0.995

Speed: 0.2ms preprocess, 8.5ms inference, 0.0ms loss, 0.8ms postprocess per image

Saving C:\acmattos\dev\tools\Python\ia4devs\runs\detect\val\predictions.json...

Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\val

🎯 Test Metrics (mean per class):

Precision: 0.958
 Recall: 0.989
 mAP@0.5: 0.980
 mAP@0.5:0.95: 0.957

image 1/1 D:\ia4devs\module_05\05_hackaton\data\sample\aws_02.png: 576x640

3 ALBs, 1 Auto Scaling, 1 Cloud Trail, 1 Cloud Watch, 1 Cloudfront, 4 EC2s,
 3 Private Subnets, 3 Public Subnets, 2 RDSS, 1 Region, 1 S3, 1 SES, 1 Users,
 2 WAFs, 1 aws, 50.6ms

Speed: 3.2ms preprocess, 50.6ms inference, 3.6ms postprocess per image at shape (1,
 3, 576, 640)

Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict

1 label saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict\labels

✓ Detailed JSON saved to data\reports\yolo11m_custom_100\results.json

✓ Summary JSON saved to data\reports\yolo11m_custom_100\report.json

[ultralytics.engine.results.Results object with attributes:

boxes: ultralytics.engine.results.Boxes object

keypoints: None

masks: None

(...)

obb: None

(...)

orig_shape: (993, 1167)

path: 'D:\\ia4devs\\module_05\\05_hackaton\\data\\sample\\aws_02.png'

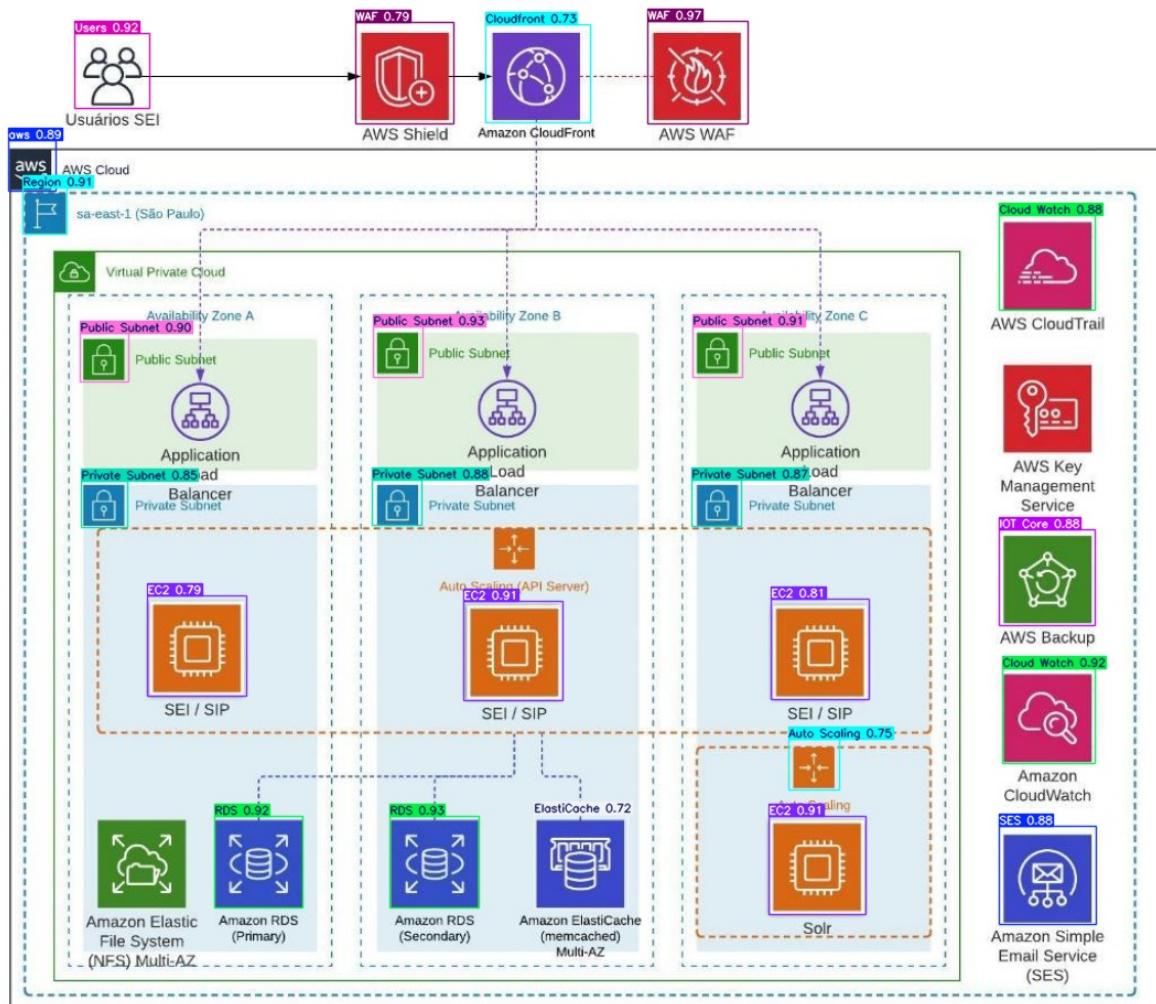
probs: None

save_dir: 'C:\\acmattos\\dev\\tools\\Python\\ia4devs\\runs\\detect\\predict'

speed: {'preprocess': 3.1897000153549016, 'inference': 50.62539997743443,
 'postprocess': 3.644100041128695}]

100% | 38.90/38.9 MB [01:27<00:00, 2.24s/MB]:

Predição do Yolo 11 - Modelo M



Detecção do Modelo M

🎯 Métricas Médias de Teste por Classe

Métrica	Modelo N	Modelo S	Modelo M
Precision	0.957	0.960	0.958
Recall	0.992	0.996	0.989
mAP@0.5	0.979	0.980	0.980
mAP@0.5:0.95	0.911	0.950	0.957

- **Nano (N):** Extremamente leve, mantém Precision/Recall/mAP@0.5 quase iguais aos demais, mas tem mAP@0.5:0.95 mais baixo (0.911), ou seja, caixas um pouco menos precisas.

- **Small (S)**: Bom equilíbrio: maior Precision/Recall, mAP@0.5 e um mAP@0.5:0.95 sólido (0.950). Ótima escolha geral para baixa latência com boa exatidão.
- **Medium (M)**: Caixa mais refinada (mAP@0.5:0.95 de 0.957), com Precision/Recall/ mAP@0.5 no mesmo patamar de S, mas exige mais recursos.

Com base nos testes, decidimos utilizar o modelo S em nosso projeto, visando o melhor desempenho com o menor gasto em recursos (disco e tempo de processamento).

Geração de Relatórios de Ameaças STRIDE

Para fazer a geração de relatórios de ameaças STRIDE, usando os modelos treinado, basta ajustar a variável abaixo:

```
trained_dir_name: str = "yolo11@_custom_100"
```

onde @ = n, s, m. Depois, execute a chamada a seguir:

```
py report_generator_test.py
```

Os relatórios podem ser encontrados [aqui](#). E o resultado da execução do script pode ser visto abaixo:

```
image 1/1 D:\ia4devs\module_05\05_hackaton\data\sample\aws_01.jpg: 544x640
1 Cloud Watch, 1 Dynamo DB, 1 Event Bus, 5 Lambdas, 1 S3, 3 SNSs, 1 Users, 1 aws,
    46.0ms
Speed: 6.2ms preprocess, 46.0ms inference, 154.7ms postprocess per image at shape (1,
    3, 544, 640)
Results saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict
1 label saved to C:\acmattos\dev\tools\Python\ia4devs\runs\detect\predict\labels
✓ Detailed JSON saved to data\reports\yolo11s_custom_100\results.json
✓ Summary JSON saved to data\reports\yolo11s_custom_100\report.json
Reports generated: data/reports/yolo11s_custom_100
```

Nosso gerador cria duas versões de relatório por análise: uma em Markdown e outra em HTML.

As ameaças STRIDE estão definidas [aqui](#). Baseado nestas definições, nosso script é capaz de categorizar e gerar o relatório para um diagrama de arquitetura AWS informado.

Aplicação Demo

Uma aplicação simples foi elaborada para demonstrar as funcionalidades desejadas para a realização deste trabalho. Ela é baseada no [Streamlit](#) e funciona da seguinte maneira:

```
streamlit run app.py
```

Após executar a chamada acima, o browser deve abrir expondo a aplicação exemplo:

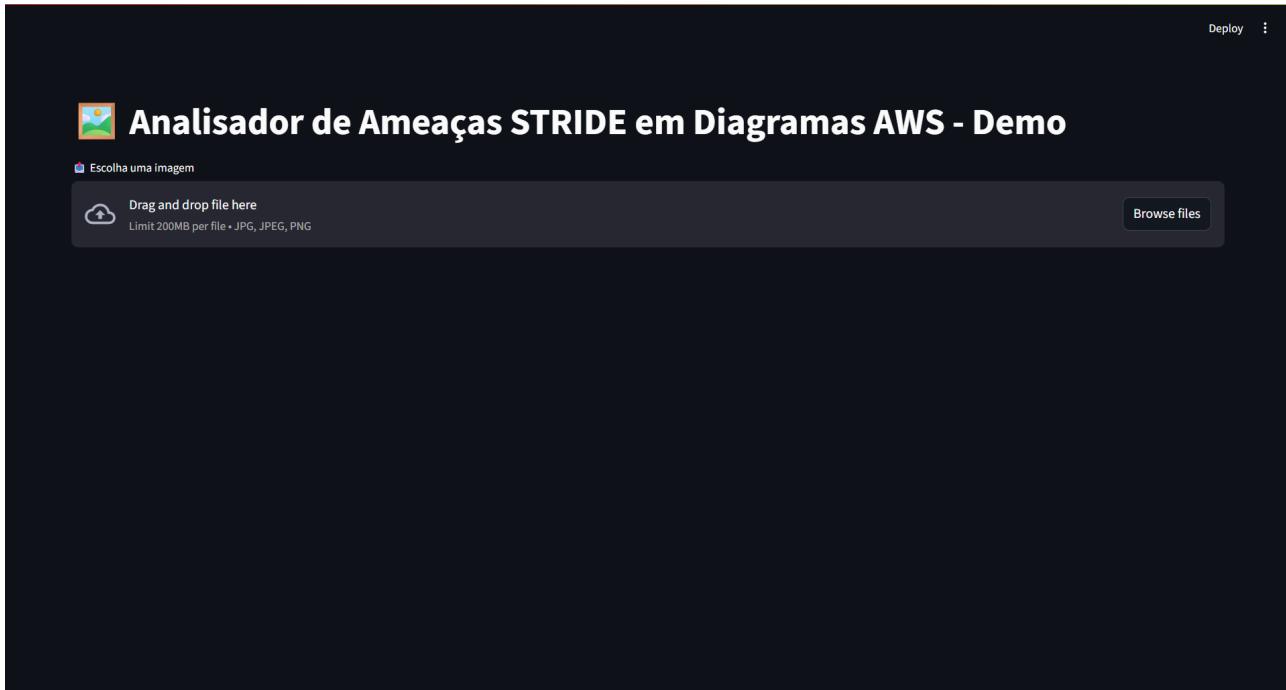


Imagen Inicial

Vamos utilizar [este arquivo exemplo](#) de arquitetura AWS. Após submetermos o arquivo exemplo para análise, vemos que a aplicação permite executar a detecção de componentes:



Imagen Detecção

Ao clicar no botão **Executar detecção**, os componentes da arquitetura são detectados pelo modelo treinado, conforme visto abaixo:



Imagen Detectado

Rolando a página, podemos ver o relatório gerado pela aplicação exemplo:

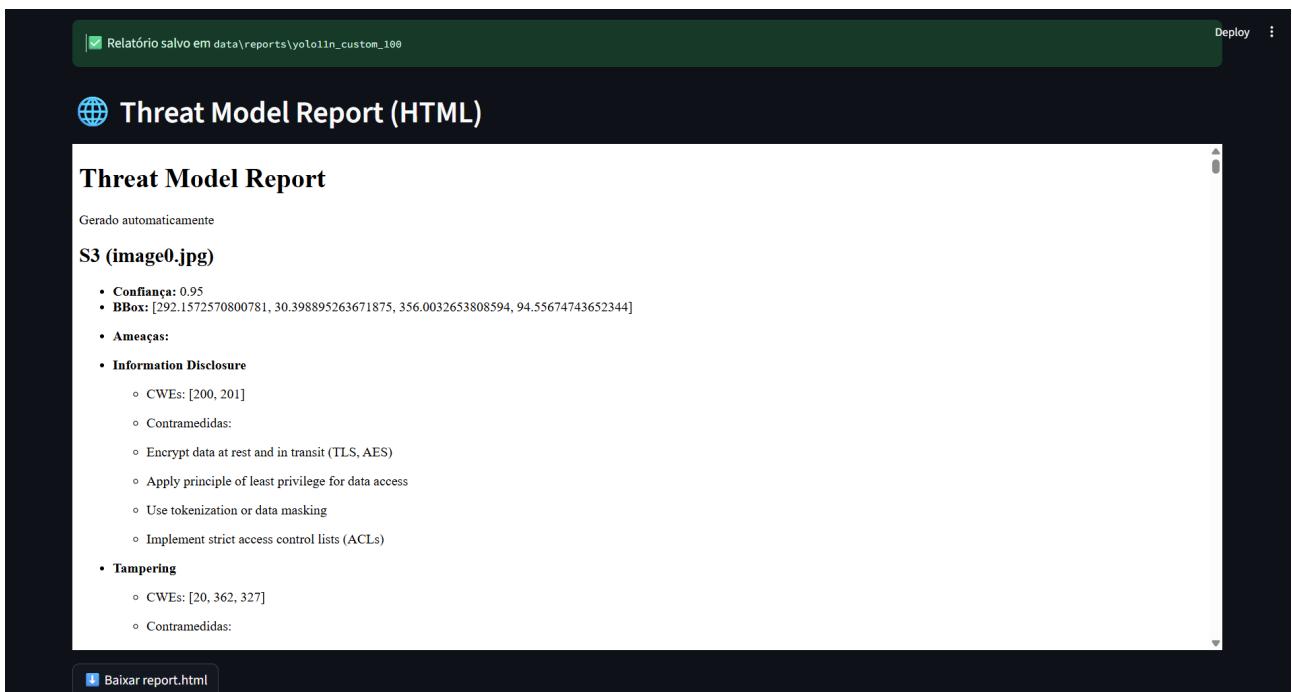


Imagen Relatório

O relatório apresentado reporta os componentes da arquitetura detectados, as ameaças STRIDE correspondentes e suas respectivas contramedidas.

Estratégia de RAG Para Aplicação Demo

Para tornar a análise de ameaças STRIDE mais contextual e precisa, foi implementado um pipeline de **RAG (Retrieval-Augmented Generation)**. A ideia é combinar um modelo de linguagem local (LLM) com uma base vetorial de conhecimento sobre segurança e STRIDE.

Essa estratégia foi considerada apenas na aplicação Demo como mais um estudo de caso de possível solução para o report.

Como funciona:

1. Indexação

O script `create-stride-rag-faiss.py` é responsável por preparar a base de conhecimento que será usada pelo sistema RAG (Retrieval-Augmented Generation). Ele realiza as seguintes etapas:

- **Leitura dos documentos PDF**

Todos os arquivos na pasta `./STRIDE-PDF/` são carregados. Esses arquivos contêm informações técnicas sobre modelagem de ameaças com STRIDE, recomendações da OWASP, boas práticas da AWS, entre outros temas relacionados à segurança de arquiteturas em nuvem.

- **Divisão em chunks**

Cada documento é segmentado em trechos menores (também chamados de *chunks*), usando uma estratégia de separação por número de tokens com sobreposição (`RecursiveCharacterTextSplitter`). Isso melhora a granularidade na busca e evita perda de contexto em trechos longos.

- **Geração de embeddings**

Cada chunk de texto é convertido em um vetor numérico (embedding) usando o modelo `"all-MiniLM-L6-v2"` da `SentenceTransformers`. Esse modelo é leve, rápido e fornece boa qualidade para recuperação semântica de textos técnicos.

- **Criação do índice FAISS**

Os embeddings são armazenados localmente utilizando o **FAISS**, uma biblioteca de indexação vetorial otimizada para busca rápida por similaridade. O índice permite que, mais tarde, quando o usuário envie um conjunto de componentes (ex: “S3”, “Lambda”, “IAM”), o sistema recupere os trechos mais relevantes desses documentos que tratam dos riscos associados a esses serviços.

-  **Armazenamento local**

O índice final é salvo no diretório `./FAISS/`, e pode ser recarregado dinamicamente pela aplicação durante o uso. Esse processo garante que o sistema tenha uma **base vetorial eficiente e contextual** para embasar a geração dos pareceres técnicos via LLM, mesmo em ambiente local e offline.

1. Consulta com LLM local

Durante a execução da aplicação, o script `stride_rag_runner.py` recebe a lista de componentes detectados no diagrama e utiliza um modelo LLM local, conectado via **Ollama**, para elaborar um relatório técnico contextualizado com base nos dados recuperados do índice FAISS.

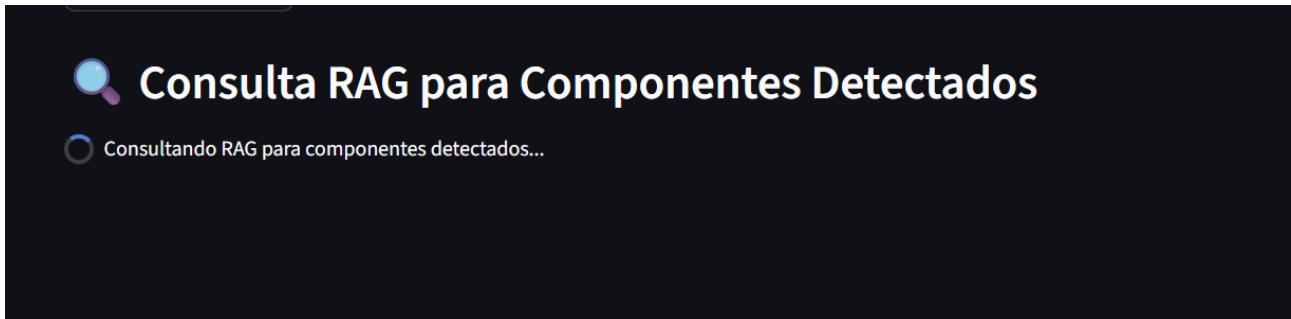
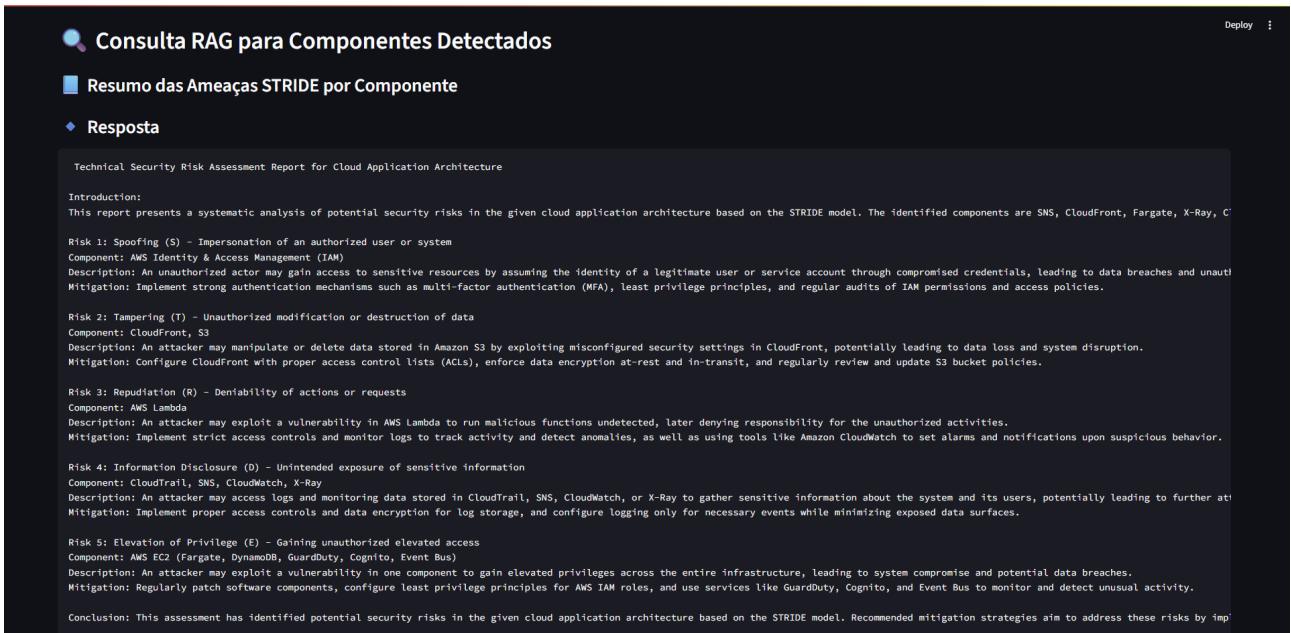


Imagen Relatório

1. Relatório Técnico com STRIDE

O modelo gera automaticamente um relatório com os possíveis riscos categorizados por tipo de ameaça STRIDE (Spoofing, Tampering, Repudiation, etc.), explicando cada caso e sugerindo formas de mitigação.



Consulta RAG para Componentes Detectados

Resumo das Ameaças STRIDE por Componente

Resposta

Technical Security Risk Assessment Report for Cloud Application Architecture

Risk 1: Spoofing (S) - Impersonation of an authorized user or system

Component: AWS Identity & Access Management (IAM)

Description: An unauthorized actor may gain access to sensitive resources by assuming the identity of a legitimate user or service account through compromised credentials, leading to data breaches and unauthorized access.

Mitigation: Implement strong authentication mechanisms such as multi-factor authentication (MFA), least privilege principles, and regular audits of IAM permissions and access policies.

Risk 2: Tampering (T) - Unauthorized modification or destruction of data

Component: CloudFront, S3

Description: An attacker may manipulate or delete data stored in Amazon S3 by exploiting misconfigured security settings in CloudFront, potentially leading to data loss and system disruption.

Mitigation: Configure CloudFront with proper access control lists (ACLs), enforce data encryption at-rest and in-transit, and regularly review and update S3 bucket policies.

Risk 3: Repudiation (R) - Deniability of actions or requests

Component: AWS Lambda

Description: An attacker may exploit a vulnerability in AWS Lambda to run malicious functions undetected, later denying responsibility for the unauthorized activities.

Mitigation: Implement strict access controls and monitor logs to track activity and detect anomalies, as well as using tools like Amazon CloudWatch to set alarms and notifications upon suspicious behavior.

Risk 4: Information Disclosure (D) - Unintended exposure of sensitive information

Component: CloudTrail, SNS, CloudWatch, X-Ray

Description: An attacker may access logs and monitoring data stored in CloudTrail, SNS, CloudWatch, or X-Ray to gather sensitive information about the system and its users, potentially leading to further attacks.

Mitigation: Implement proper access controls and data encryption for log storage, and configure logging only for necessary events while minimizing exposed data surfaces.

Risk 5: Elevation of Privilege (E) - Gaining unauthorized elevated access

Component: AWS EC2 (Fargate, DynamoDB, GuardDuty, Cognito, Event Bus)

Description: An attacker may exploit a vulnerability in one component to gain elevated privileges across the entire infrastructure, leading to system compromise and potential data breaches.

Mitigation: Regularly patch software components, configure least privilege principles for AWS IAM roles, and use services like GuardDuty, Cognito, and Event Bus to monitor and detect unusual activity.

Conclusion: This assessment has identified potential security risks in the given cloud application architecture based on the STRIDE model. Recommended mitigation strategies aim to address these risks by implementing appropriate security controls and monitoring measures.

Imagen Relatório

1. Ao final é exibido a fonte consultada:

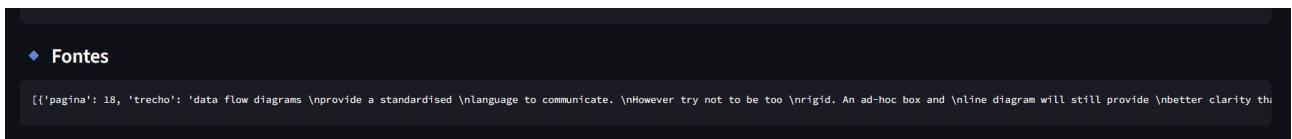


Imagen Relatório

Requisitos

Para que o modelo funcione corretamente:

- Instale o **Ollama** em sua máquina:
 [Download Ollama para Windows](#)
- Execute o servidor com o modelo desejado, por exemplo:
```bash ollama run mistral

Obs.: A aplicação demo funcionará sem o RAG caso o Ollama não seja instalado.

## Estratégia de RAG Para Aplicação Demo

Para tornar a análise de ameaças STRIDE mais contextual e precisa, foi implementado um pipeline de **RAG (Retrieval-Augmented Generation)**. A ideia é combinar um modelo de linguagem local (LLM) com uma base vetorial de conhecimento sobre segurança e STRIDE.

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-  **Divisão em chunks**

Cada documento é segmentado em trechos menores (também chamados de *chunks*), usando uma estratégia de separação por número de tokens com sobreposição (`RecursiveCharacterTextSplitter`). Isso melhora a granularidade na busca e evita perda de contexto em trechos longos.

-  **Geração de embeddings**

Cada chunk de texto é convertido em um vetor numérico (embedding) usando o modelo "`all-MiniLM-L6-v2`" da `SentenceTransformers`. Esse modelo é leve, rápido e fornece boa qualidade para recuperação semântica de textos técnicos.

-  **Criação do índice FAISS**

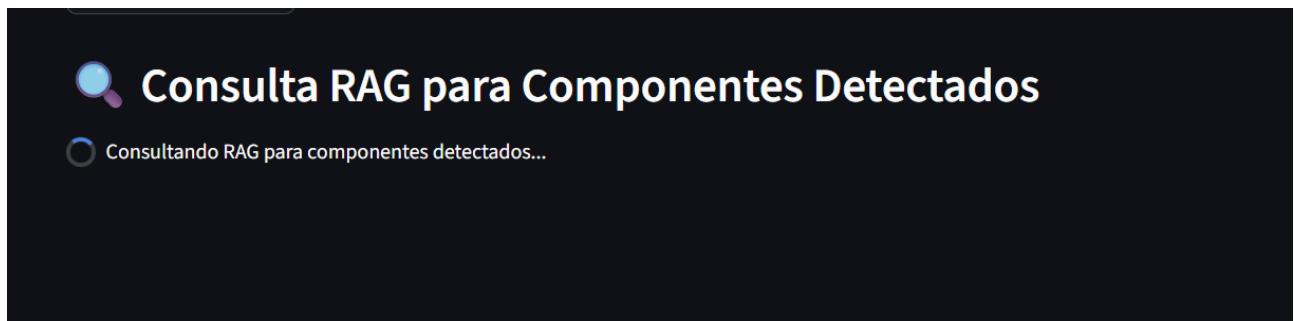
Os embeddings são armazenados localmente utilizando o **FAISS**, uma biblioteca de indexação vetorial otimizada para busca rápida por similaridade. O índice permite que, mais tarde, quando o usuário envie um conjunto de componentes (ex: "S3", "Lambda", "IAM"), o sistema recupere os trechos mais relevantes desses documentos que tratam dos riscos associados a esses serviços.

-  **Armazenamento local**

O índice final é salvo no diretório `./FAISS/`, e pode ser recarregado dinamicamente pela aplicação durante o uso. Esse processo garante que o sistema tenha uma **base vetorial eficiente e contextual** para embasar a geração dos pareceres técnicos via LLM, mesmo em ambiente local e offline.

## 1. Consulta com LLM local

Durante a execução da aplicação, o script `stride_rag_runner.py` recebe a lista de componentes detectados no diagrama e utiliza um modelo LLM local, conectado via [Ollama](#), para elaborar um relatório técnico contextualizado com base nos dados recuperados do índice FAISS.



*Imagen Relatório*

## 1. Relatório Técnico com STRIDE

O modelo gera automaticamente um relatório com os possíveis riscos categorizados por tipo de ameaça STRIDE (Spoofing, Tampering, Repudiation, etc.), explicando cada caso e sugerindo formas de mitigação.

 Consulta RAG para Componentes Detectados

Deploy ⚙

Resumo das Ameaças STRIDE por Componente

♦ Resposta

Technical Security Risk Assessment Report for Cloud Application Architecture

Introduction:  
This report presents a systematic analysis of potential security risks in the given cloud application architecture based on the STRIDE model. The identified components are SNS, CloudFront, Fargate, X-Ray, C...

Risk 1: Spoofing (S) - Impersonation of an authorized user or system  
Component: AWS Identity & Access Management (IAM)  
Description: An unauthorized actor may gain access to sensitive resources by assuming the identity of a legitimate user or service account through compromised credentials, leading to data breaches and unauthorized access.  
Mitigation: Implement strong authentication mechanisms such as multi-factor authentication (MFA), least privilege principles, and regular audits of IAM permissions and access policies.

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Component: CloudFront, S3  
Description: An attacker may manipulate or delete data stored in Amazon S3 by exploiting misconfigured security settings in CloudFront, potentially leading to data loss and system disruption.  
Mitigation: Configure CloudFront with proper access control lists (ACLs), enforce data encryption at-rest and in-transit, and regularly review and update S3 bucket policies.

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Component: AWS Lambda  
Description: An attacker may exploit a vulnerability in AWS Lambda to run malicious functions undetected, later denying responsibility for the unauthorized activities.  
Mitigation: Implement strict access controls and monitor logs to track activity and detect anomalies, as well as using tools like Amazon CloudWatch to set alarms and notifications upon suspicious behavior.

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Component: CloudTrail, SNS, CloudWatch, X-Ray  
Description: An attacker may access logs and monitoring data stored in CloudTrail, SNS, CloudWatch, or X-Ray to gather sensitive information about the system and its users, potentially leading to further attacks.  
Mitigation: Implement proper access controls and data encryption for log storage, and configure logging only for necessary events while minimizing exposed data surfaces.

Risk 5: Elevation of Privilege (E) - Gaining unauthorized elevated access  
Component: AWS EC2 (Fargate, DynamoDB, GuardDuty, Cognito, Event Bus)  
Description: An attacker may exploit a vulnerability in one component to gain elevated privileges across the entire infrastructure, leading to system compromise and potential data breaches.  
Mitigation: Regularly patch software components, configure least privilege principles for AWS IAM roles, and use services like GuardDuty, Cognito, and Event Bus to monitor and detect unusual activity.

Conclusion: This assessment has identified potential security risks in the given cloud application architecture based on the STRIDE model. Recommended mitigation strategies aim to address these risks by im...

*Imagen Relatório*

1. Ao final é exibido a fonte consultada:

♦ Fontes

```
[{"pagina": 18, "trecho": "data flow diagrams \nprovide a standardised \nlanguage to communicate. \n\nHowever try not to be too \nrigid. An ad-hoc box and \nline diagram will still provide \nbetter clarity th..."}]
```

*Imagen Relatório*

## Requisitos

Para que o modelo funcione corretamente:

- Instale o **Ollama** em sua máquina:  
 [Download Ollama para Windows](#)
- Execute o servidor com o modelo desejado, por exemplo:  
```bash ollama run mistral

Obs.: A aplicação demo funcionará sem o RAG caso o Ollama não seja instalado.

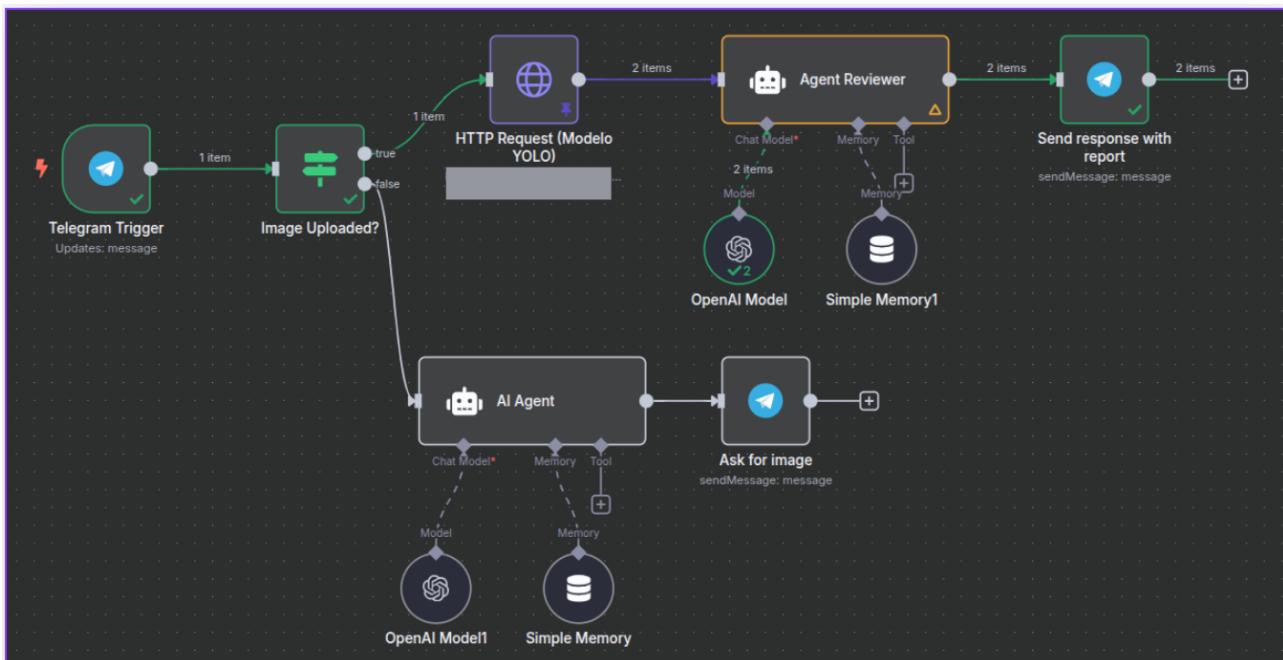
Arch Wise - Agente de feedback de arquitetura



Agente de Arch Wise

Um agente de feedback foi desenvolvido para utilização do modelo YOLO 11 (small) treinado para avaliar diagramas de arquitetura AWS. Este agente é capaz de receber um diagrama por meio do Telegram, enviar para o modelo treinado e por fim, enviar o resultado de volta para o usuário do Telegram. Esta solução foi desenvolvida utilizando uma API escrita em Flask e hospedada num Droplet da Digital Ocean.

Arquitetura



Arquitetura do workflow do N8N

A arquitetura do agente de feedback é composta por quatro componentes principais:

- **API:** API escrita em Flask que recebe o diagrama do usuário e envia para o modelo treinado.
- **Modelo:** Modelo YOLO 11 (small) treinado para detecção de componentes de arquitetura AWS.
- **Telegram:** Interface com o usuário via Telegram.
- **N8N:** Workflow de automação, responsável por orquestrar todas as etapas deste agente.

API

A API é responsável por receber o diagrama do usuário e enviar para o modelo treinado, que está sendo chamado através da API Flask. Este endpoint é chamado como um dos passos do workflow de automação do N8N.

Definições da API:

- **Endpoint:** /architecture-detect
- **Método:** POST
- **Body:** image (base64), chat_details (json)
- **Response:** json

O body da requisição é composto por:

- **image :** base64 da imagem do diagrama de arquitetura AWS.

- `chat_details` : detalhes do chat do usuário, incluindo o ID do chat e o ID do usuário.

O response da requisição é composto por:

- `status` : status da requisição:
 - `201` : sucesso.
 - `400` : erro de requisição.
 - `500` : erro interno do servidor.
- `message` : mensagem de resposta.
- `markdown_report` : relatório de ameaças STRIDE em formato Markdown.

Modelo

O modelo YOLO 11 (small) treinado para detecção de componentes de arquitetura AWS é responsável por receber o diagrama do usuário e enviar e gerar um relatório de ameaças STRIDE em formato Markdown.

Agent Reviewer

Este agente faz parte de um dos passos do workflow do N8N. Ele é responsável por receber o relatório de ameaças STRIDE, realizar uma análise que inclui os seguintes pontos do relatório gerado pelo modelo YOLO 11:

- **Ameaças:** Ameaças STRIDE encontradas no diagrama.
- **Overview de Arquitetura:** Overview de arquitetura AWS, com os componentes detectados e suas respectivas ameaças STRIDE.
- **Matrix de Ameaças:** Matrix de ameaças, com uma lista de ameaças divididas por impacto, risco e categoria.
- **Recomendações de priorização:** Recomendações para melhoria da arquitetura, baseadas no nível do risco que cada ameaça representa.
- **Possível roadmap de melhoria:** Possível roadmap de melhoria da arquitetura, criando um planejamento e plano de ação de acordo com as recomendações de priorização.
- **Próximos passos:** Com as ameaças identificadas, o agente deve sugerir os próximos passos para desenvolvimento da estratégia de mitigação.

Telegram

Um bot foi criado para permitir a interação entre o agente e o usuário. Este bot é responsável por receber as mensagens do usuário, imagens de diagramas de arquitetura AWS e enviar para o agente de feedback.

N8N

O N8N é responsável por orquestrar todas as etapas deste agente. As etapas são:

- **Receber mensagem do usuário enviada no Telegram:** O N8N recebe a mensagem do usuário e verifica se é uma imagem de diagrama de arquitetura AWS.
- **Enviar imagem para o modelo:** O N8N envia a imagem para o modelo YOLO 11 (small) treinado para detecção de componentes de arquitetura AWS, via endpoint da API.
- **Receber relatório do modelo:** O N8N recebe o relatório de ameaças STRIDE em formato Markdown do modelo YOLO 11 (small) treinado para detecção de componentes de arquitetura AWS.
- **Enviar relatório para o agente de review:** O N8N envia o relatório de ameaças STRIDE em formato Markdown para o agente de review.
- **Relatório melhorado:** O agente de review realiza uma análise do relatório gerado pelo modelo YOLO 11 (small) e gera um relatório melhorado, com base nos pontos mencionados anteriormente.
- **Enviar relatório para o usuário:** O N8N envia final, gerado pelo agente de review, para o usuário.

Testar o agente: Caso queira testar o agente, basta enviar uma mensagem para o bot do Telegram **bot_arch_wise** com o comando `/start`.