

AI-Augmented Virtual Tumor Board with Integrated Patient Imaging Upload and Progressive Disclosure Visualization

A Human-Centered Design for Democratizing Oncology Decision Support

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github.com/inventcures/virtual-tumor-board

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Abstract

Tumor board meetings are essential for multidisciplinary cancer care, yet access remains limited by geography, expertise availability, and economic factors—particularly in resource-constrained settings like India. We present an open-source AI-augmented Virtual Tumor Board (VTB) system featuring: (1) a complete patient upload workflow for medical documents and imaging, (2) multi-agent deliberation with seven specialty-specific AI agents, (3) MedGemma integration for medical image analysis supporting DICOM and phone-captured imaging, and (4) progressive disclosure visualization adapting to four expertise levels. Our V8 architecture introduces an integrated upload flow where patients can submit pathology reports, radiology reports, genomic testing, AND actual medical images (CT/MRI/X-ray) through DICOM upload, phone camera capture, or gallery selection. Dr. Chitran, our AI radiologist agent, receives full MedGemma analysis for reconciliation with uploaded radiology reports, while other specialists receive imaging summaries for treatment planning context. The system implements RECIST 1.1 for response assessment and provides interactive visualizations including waterfall plots, swimmer plots, and anatomical heat maps. This paper details the complete system architecture, user workflow design, and implica-

tions for democratizing expert oncology decision support across diverse healthcare settings.

Keywords: Tumor Board, Multi-Agent Systems, Medical Imaging Upload, MedGemma, Progressive Disclosure, RECIST 1.1, Human-Centered Design, Low-Resource Healthcare, India

1 Introduction

1.1 The Access Gap in Oncology Care

Multidisciplinary tumor boards (MTBs) represent the gold standard for cancer treatment planning, bringing together surgical oncology, medical oncology, radiation oncology, radiology, pathology, genetics, and palliative care specialists [1]. However, access to comprehensive tumor boards remains highly inequitable:

- Only 23% of cancer patients in India have access to formal tumor board review
- Average case preparation requires 47 minutes per complex case
- Subspecialty oncologists are concentrated in tier-1 cities
- Many patients travel 200+ km for expert consultation

1.2 The Patient Data Challenge

A critical barrier to virtual tumor boards is data aggregation. Patients in India often arrive with:

- Handwritten OPD prescriptions containing staging information
- Paper pathology reports from local laboratories
- Photos of radiology reports on their phones
- Actual CT/MRI films or CDs that remain unread
- Mixed documents spanning multiple hospitals

Existing telemedicine solutions focus on video consultation but lack infrastructure for structured clinical data extraction and imaging analysis.

1.3 Our Contribution

This paper presents the Virtual Tumor Board system with the following contributions:

1. A **complete patient upload workflow** spanning document classification, imaging upload, and AI-powered data extraction
2. **Integrated medical imaging** supporting DICOM files, phone camera capture, and gallery upload with MedGemma analysis
3. **Multi-agent deliberation** with seven specialty agents, including Dr. Chitran (radiologist) with enhanced imaging reconciliation capabilities
4. **Progressive disclosure visualization** adapting complexity across patient, clinician, oncologist, and radiologist expertise levels
5. A **completeness scoring system** that quantifies data availability and communicates limitations to users and AI agents
6. **Open-source implementation** designed for deployment on low-cost infrastructure

2 System Architecture

2.1 High-Level Overview

Figure 1 presents the complete system architecture organized into four primary layers:

1. **User Upload Layer:** Document and imaging upload with AI classification
2. **Presentation Layer:** React/Next.js web application with visualization components
3. **Orchestration Engine:** Multi-agent deliberation with MedGemma integration
4. **Knowledge Layer:** Clinical guideline retrieval via RAG

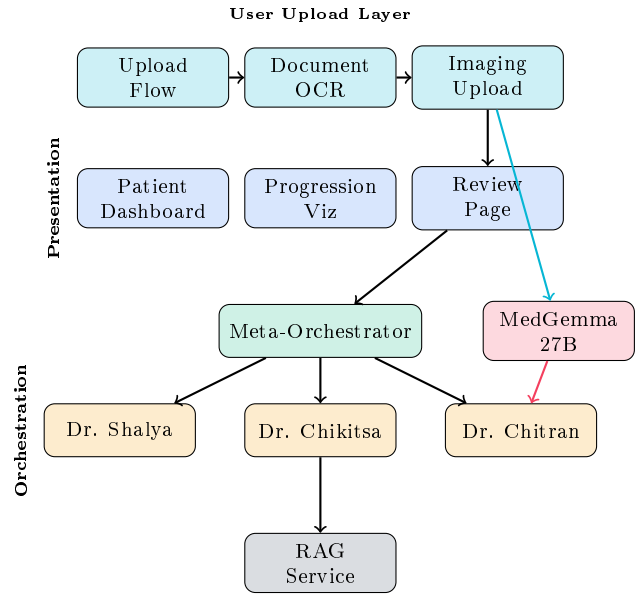


Figure 1: System architecture showing the four-layer design with integrated imaging upload and MedGemma analysis feeding into Dr. Chitran’s deliberation.

2.2 User Upload Workflow

The upload workflow guides users through a four-step process designed for accessibility on mobile devices:

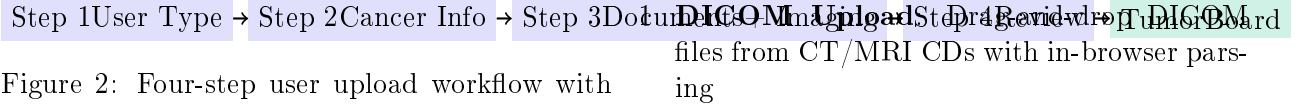


Figure 2: Four-step user upload workflow with integrated imaging.

2.2.1 Step 1: User Type Selection

Users identify as one of three personas:

- **Patient/Caregiver:** Receives simplified language, guidance on document types
- **Oncologist:** Seeking second opinion, expects full technical detail
- **Non-Oncology Doctor:** Referring patient, needs actionable summary

2.2.2 Step 2: Cancer Site and Staging

Users select cancer site from India-prevalent cancers first (oral cavity, cervix, stomach, esophagus, gallbladder) or use “auto-detect” for AI-based classification from uploaded documents.

2.2.3 Step 3: Document and Imaging Upload

This step combines two critical functions:

Document Upload Users upload photos or PDFs of medical records. The system provides:

- AI-powered document classification (pathology, radiology report, genomics, prescription, etc.)
- OCR with support for handwritten Indian medical abbreviations (HPE, FNAC, IHC, NACT, etc.)
- Clinical data extraction (histology, grade, biomarkers, mutations)
- Progress indicator with pipeline stages

Medical Imaging Upload A collapsible section allows upload of actual medical images through three methods:

1. **DICOM Upload:** Upload DICOM files from CT/MRI CDs with in-browser parsing
2. **Phone Camera:** Capture photos of X-rays, CT films, or physical scans with quality validation
3. **Gallery Selection:** Upload existing photos from device gallery

Each uploaded image receives immediate MedGemma AI analysis with:

- Finding detection and description
- Measurement extraction
- Oncologic impression
- Confidence score

2.2.4 Step 4: Completeness Review

The review page presents:

- Completeness score (0-100%) based on uploaded document types
- Missing critical documents with clinical impact explanation
- Imaging studies with AI analysis status
- Agent limitations due to missing data

2.3 Session Data Model

The upload session (UploadSessionV6) stores:

```
interface UploadSessionV6 {
  id: string;
  userType: 'patient' | 'oncologist' | 'doctor';
  cancerSite: string;
  staging: StagingInfo;
  documents: UploadedDocument[];
  imagingStudies: UploadedImagingStudy[];
  hasUserUploadedImaging: boolean;
  imagingConsentAccepted: boolean;
  completeness: CompletenessResult;
  autoStageResult?: AutoStageResult;
}
```

3 MedGemma Integration

3.1 Model Selection

We integrate Google’s MedGemma 27B model for medical image analysis with a priority-based provider selection:

1. **Vertex AI Model Garden:** Primary provider for production deployments
2. **HuggingFace Space:** Fallback using Ze-roGPU for cost-effective access
3. **Gemini Pro Vision:** Final fallback for general image understanding

3.2 Analysis Pipeline

For each uploaded image:

1. Image preprocessing (windowing for DICOM, enhancement for photos)
2. MedGemma inference with oncology-specific prompting
3. Structured response parsing (findings, measurements, impression)
4. Storage in session for deliberation

3.3 Dr. Chitran Enhanced Integration

Dr. Chitran (AI Radiologist) receives enhanced context when images are available:

```
## IMAGING DATA AVAILABLE

### MedGemma AI Analysis
- Findings: [list with severity]
- Measurements: [sizes, locations]
- Impression: [AI interpretation]
- Confidence: [percentage]

### YOUR RECONCILIATION TASK
1. Compare AI analysis with radiology reports
2. Flag measurement discrepancies (>20%)
3. Note new findings detected by AI
4. Assess clinical significance
```

Other agents receive a summarized imaging context to inform their specialty opinions.

4 Completeness Scoring

4.1 Algorithm

Completeness is calculated based on cancer-site-specific document requirements:

Algorithm 1 Completeness Score Calculation

Require: Documents D , CancerSite C , HasImaging I

- 1: $critical \leftarrow C.requiredDocs.critical$
- 2: $recommended \leftarrow C.requiredDocs.recommended$
- 3: $criticalMet \leftarrow |critical \cap D|$
- 4: $recommendedMet \leftarrow |recommended \cap D|$
- 5: **if** I **and** ‘radiology’ \in missing **then**
- 6: $criticalMet \leftarrow criticalMet + 0.5$ ▷ Partial credit
- 7: **end if**
- 8: $score \leftarrow 0.6 \times \frac{criticalMet}{|critical|} + 0.4 \times \frac{recommendedMet}{|recommended|}$
- 9: **return** $score \times 100$

4.2 Agent Limitation Communication

Missing documents translate to explicit agent limitations:

Missing Doc	Agent Limitation
Pathology	Dr. Marga cannot confirm histology; Dr. Chikitsa cannot recommend specific systemic therapy
Radiology (no imaging)	Dr. Chitran cannot assess staging; surgical/radiation planning limited
Radiology (with imaging)	No formal report, but AI analysis available
Genomics	May miss targeted therapy options
Lab reports	Cannot assess organ function for chemo eligibility

Table 1: Agent limitations based on missing documents.

5 Multi-Agent Deliberation

5.1 Agent Configuration

Seven specialist agents participate in deliberation:

Agent	Specialty	Enhanced Capabilities
Dr. Shalya	Surgical Oncology	Resectability, timing
Dr. Chikitsa	Medical Oncology	Systemic therapy, trials
Dr. Kirann	Radiation Oncology	RT planning, technique
Dr. Chitran	Onco-Radiology	MedGemma reconciliation
Dr. Marga	Pathology	Biomarker interpretation
Dr. Anuvamsha	Genetics	Targeted therapy matching
Dr. Shanti	Palliative Care	Symptom management

Table 2: Specialist agents with V8 enhanced capabilities.

5.2 Imaging-Aware Deliberation

When imaging is uploaded, deliberation includes:

1. Dr. Chitran receives full MedGemma analysis for expert reconciliation
2. Other agents receive imaging summary (impression, key measurements)
3. Case info includes imaging status: study count, analysis completion
4. Consensus addresses imaging-based staging and response assessment

6 Progressive Disclosure Visualization

6.1 Four-Level Expertise Adaptation

We maintain the four-level progressive disclosure framework:

1. **Patient:** Traffic light metaphor, plain language, journey timeline
2. **Clinician:** Metrics, waterfall chart, clinical actions
3. **Oncologist:** RECIST details, spider plots, per-lesion tracking
4. **Radiologist:** Full measurement matrix, study comparison, DICOM metadata

6.2 Interactive Visualizations

- **Waterfall Chart:** Percent change per lesion with RECIST thresholds
- **Swimmer Plot:** Treatment timeline with response segments
- **Spider Plot:** Individual lesion trajectories over time
- **Anatomical Heat Map:** Body silhouette with lesion markers
- **Response Donut:** Proportional response category distribution

7 Implementation

7.1 Technology Stack

- **Frontend:** Next.js 15, React 19, Tailwind CSS
- **DICOM:** dicom-parser (client-side parsing)
- **AI Orchestration:** Claude 3.5 Sonnet / Gemini 2.0 Flash
- **Medical Imaging:** MedGemma 27B (Vertex AI / HF Space)
- **RAG:** Gemini File Search API
- **Deployment:** Railway (serverless)
- **Storage:** localStorage (session), R2 (optional server)

7.2 Mobile Optimization

Given that most Indian users access healthcare via mobile:

- Touch-optimized upload dropzone with large tap targets
- Camera capture with quality validation (blur, lighting)
- Image compression before upload (max 1600px)

- Progressive loading of visualization components
- Offline-capable document storage via IndexedDB

7.3 Privacy Considerations

- PHI consent dialog before imaging upload
- Client-side DICOM parsing (no server upload)
- Session auto-expiry after 24 hours
- No permanent storage of patient data
- Images processed via API, not stored long-term

8 Discussion

8.1 Design Decisions

8.1.1 Unified Upload vs. Separate Flows

We chose to integrate imaging upload within the document upload page rather than creating a separate flow. This reduces user friction and ensures imaging context is available alongside clinical documents.

8.1.2 Consent Before Imaging

A dedicated consent dialog addresses:

- Educational purpose disclaimer
- AI limitation acknowledgment
- Data handling transparency
- Emergency guidance

8.1.3 Partial Credit for Imaging

When radiology *reports* are missing but actual *imaging* is uploaded, the system:

- Provides 50% credit toward radiology requirement
- Enables Dr. Chitran to provide opinion (with caveats)
- Notes absence of formal radiologist interpretation

8.2 Limitations

1. MedGemma accuracy on phone-captured images requires clinical validation
2. Multi-agent latency (30-60 seconds) unsuitable for urgent cases
3. localStorage constraints limit session size (5MB)
4. Requires internet for AI features
5. RECIST requires manual lesion correspondence confirmation

8.3 Future Work

1. Clinical validation studies in Indian cancer hospitals
2. PACS integration for seamless DICOM import
3. Volumetric RECIST (vRECIST) implementation
4. Multilingual support (Hindi, Tamil, Bengali)
5. Mobile-native application
6. Federated learning for improved MedGemma accuracy

9 Conclusion

We presented the Virtual Tumor Board V8 system with integrated patient imaging upload and MedGemma analysis. By combining structured document upload, medical imaging analysis, multi-agent deliberation, and progressive disclosure visualization, our system democratizes access to comprehensive tumor board review. The integrated workflow reduces barriers for patients in resource-limited settings while maintaining clinical rigor through explicit data limitation communication and agent-aware recommendations. Our open-source implementation provides a foundation for expanding AI-augmented oncology care globally.

Acknowledgments

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Code Availability

Source code: <https://github.com/inventcures/virtual-tumor-board>
Live demo: <https://virtual-tumor-board.up.railway.app>

References

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- [3] Google Health. MedGemma: Open Models for Medical Image Understanding. 2025.
- [4] Dattani S. Saloni’s Guide to Data Visualization. December 2025.
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A Upload Session Type Definition

```
export interface UploadSessionV6 extends UploadSessionV5 {
  imagingStudies?: UploadedImagingStudy[];
  extractedRadiologyReports?: ExtractedRadiologyReport[];
  hasUserUploadedImaging: boolean;
  imagingConsentAccepted: boolean;
  recistBaseline?: {
    studyId: string;
    studyDate: string;
    targetLesionSum: number;
  };
};

export interface UploadedImagingStudy {
  study: ImagingStudy;
  medGemmaAnalysis?: MedGemmaResponse;
  uploadedAt: string;
  status: 'pending' | 'analyzing' | 'complete' | 'error';
}
```

B Dr. Chitran Enhanced Prompt

```
## ENHANCED IMAGING REVIEW CAPABILITIES

When Images ARE Uploaded (MedGemma Available):

1. Review MedGemma AI Analysis
  - Examine findings, measurements, impressions
  - Note confidence levels and limitations

2. Compare with Radiology Reports (if available)
  - Identify concordance/discrepancies
  - FLAG measurement differences >20%

3. Provide Expert Reconciliation
  - Which interpretation is more likely correct
  - Whether discrepancies affect management

### Output Structure:
- IMAGING DATA SOURCES checklist
- KEY FINDINGS SUMMARY (integrated)
- AI vs REPORT COMPARISON table
- SIGNIFICANT DISCREPANCIES list
- STAGING ASSESSMENT
- RESPONSE ASSESSMENT (if follow-up)
- RECOMMENDATIONS
- CONFIDENCE LEVEL with basis
```

C Completeness Scoring Implementation

```
function calculateCompleteness(
  uploadedTypes: DocumentType[],
  cancerSiteId: string,
  hasImagingStudies: boolean = false
): CompletenessResult {
  const cancerSite = getCancerSiteById(cancerSiteId);
  // ... check critical and recommended docs

  // Partial credit for imaging
  if (hasImagingStudies) {
    if (radiologyMissingCritical) criticalMet += 0.5;
    if (radiologyMissingRecommended) recommendedMet += 0.5;
  }

  // Critical 60%, Recommended 40%
  const score = criticalScore + recommendedScore;

  // Get agent limitations with imaging awareness
  const limitations = getAgentLimitations(missing, hasImagingStudies);

  return { completenessScore: score, ... };
}
```